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A socio-technical exploration of the Car as Power Plant

Park Lee, E.H.

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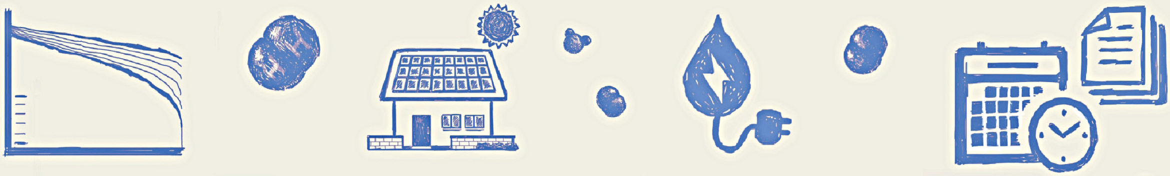
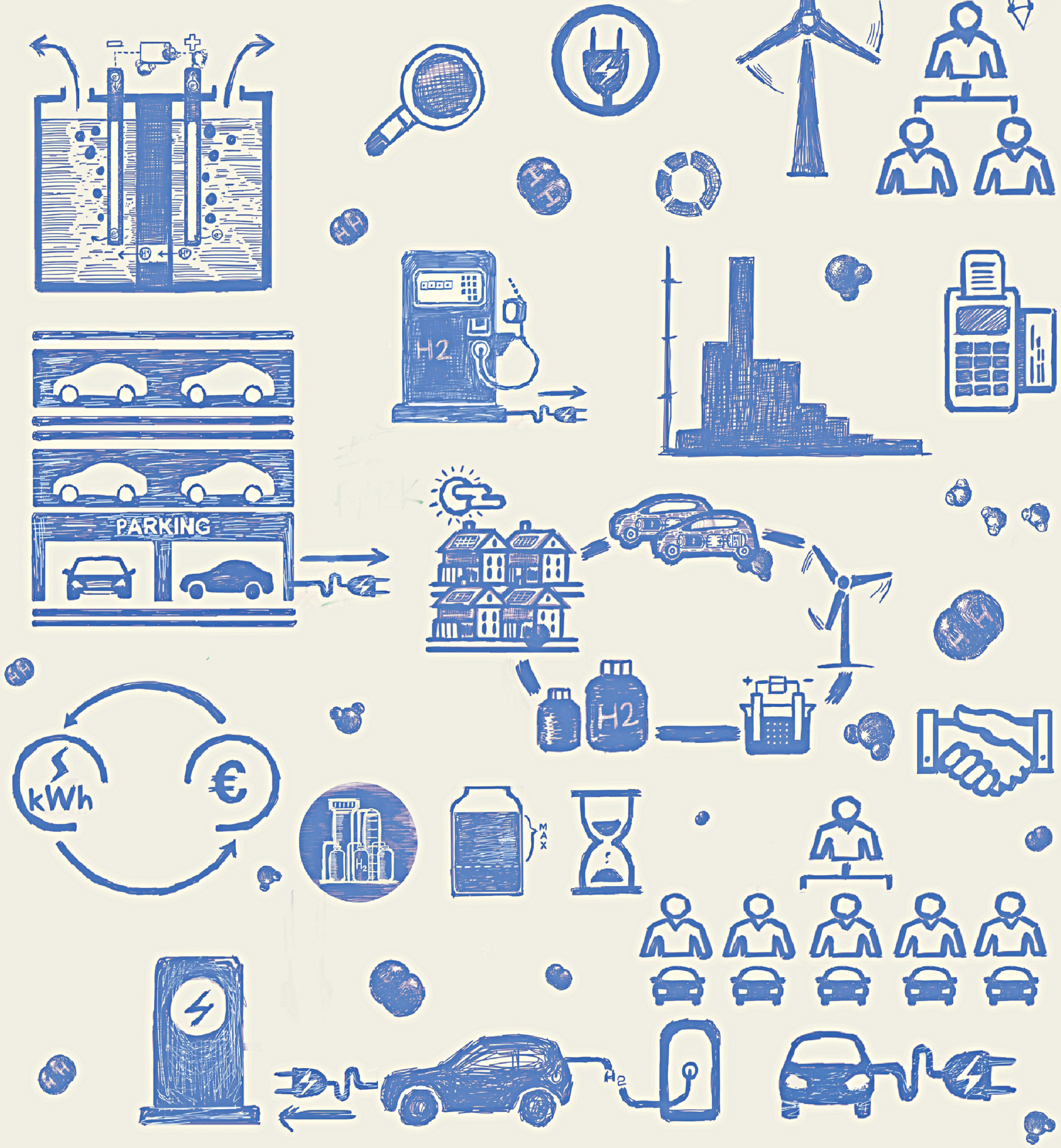


A socio-technical exploration of the Car as Power Plant

Esther Hae-Kyung PARK LEE



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A socio-technical exploration of the Car as Power Plant

Dissertation

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by

Hae-Kyung PARK LEE

Master of Science in Industrial Ecology,
Leiden University and Delft University of Technology
born in Barcelona, Spain

The dissertation has been approved by the promotors:

Prof. dr.ir. Z. Lukszo
Prof. dr.ir. P. M. Herder

Composition of the doctoral committee:

Rector Magnificus	chairperson
Prof.dr.ir. Z. Lukszo	Delft University of Technology, promotor
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Keywords: vehicle-to-grid, contracts, fuel cell electric vehicles, socio-technical systems, agent-based modeling and simulation.

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Summary

Introduction

In the transition towards low-carbon energy systems, the growth of variable renewable energy sources (V-RES) like solar and wind in the electricity systems is calling for more flexibility measures. These are needed to cope with the increased uncertainty and variability that affects the residual demand. Flexibility can be offered by traditional players in the sector, through dispatchable generation, storage, demand response, and increased interconnection. However, there are also increasing opportunities for new actors and roles. Aggregators, for example, can exploit the flexibility of small consumers and trade it on their behalf in the electricity markets. This flexibility can also be provided from other sectors, such as heating and transportation. With the adoption and diffusion of electric vehicles, the aggregated capacity is considered to have significant potential to support the grid in the future. Vehicles are only used 5% of the time for driving. Thus, when parked, they could be used for providing flexibility through storage or providing vehicle-to-grid (V2G) power.

The Car as Power Plant (CaPP) concept proposes integrated energy and transport systems based on renewable energy, hydrogen, and Fuel Cell Electric Vehicles (FCEVs). In this concept, hydrogen is used for storage of renewable electricity, for transportation and re-electrification. Parked FCEVs can be used to provide flexible electricity through V2G. In this context, vehicle owners and drivers become *prosumers* in the electricity system. From a socio-technical systems view, the availability of FCEVs for V2G is not only constrained by the drivers' driving needs, but also their willingness to participate. Prosumers, with their different actions and participation preferences, have to be considered when analyzing the feasibility of the vehicle-to-grid concept. More importantly, the rules needed for managing these V2G transactions have to be defined. This research explored the operation of fuel cell cars for V2G in Car as Power Plant systems, from a socio-technical system perspective. The main research question addressed was *"How can prosumers' FCEVs be the leveraged as flexibility sources within Car as Power Plant systems?"*. This question was answered through four distinct perspectives: 1) Role of institutions in vehicle-to-grid implementation, 2) Implications of vehicle-to-grid participation, 3) Conceptualization of vehicle-to-grid contracts, and 4) Performance of vehicle-to-grid contracts.

Role of institutions in vehicle-to-grid implementation

Institutions are defined as the rules that structure social interactions. In this research, we classified institutions according to Williamson's four-layer framework. In the literature review, we explored the role of institutions in vehicle-to-grid implementation by analyzing the literature that focuses on one or more institutional layers. The literature topics were classified into three categories: 1) Techno-economic assessments, 2) V2G

contracts, and 3) Institutional environment. The three institutional perspectives showed the role of institutions in vehicle-to-grid implementation from different timescales and perspectives. At the operational timescale, the management of V2G transactions is explored with the use of contracts. We found that interactions between contracts, physical system operation, and actor behavior are not explored in the literature. In general, the socio-technical systems perspective is rare in the literature, as usually the characteristics and behavior of the actors are not addressed. This thesis extensively explored the role of contracts in the operation of CaPP systems from a socio-technical systems perspective.

Implications of vehicle-to-grid participation

To better understand the implications of V2G for drivers, we explored the operation of a Car as Power Plant microgrid focusing on the physical system operation. The availability of vehicles for V2G was defined by each car's driving schedule which was derived from real world mobility data. Thus, cars were assumed to be available whenever in the neighborhood. Driving schedules also defined the changing levels of fuel and the minimum fuel needs for driving. The results showed that vehicles ended up being available on average for 50% of the time and each vehicle was used only a fifth of that time. The 'capacity factor' of fuel cell vehicles, however, showed seasonal fluctuations, following the residual demand. The results highlighted the importance of vehicle availability in systems where FCEVs are used for reliability purposes. Moreover, we concluded that the autonomy loss is high when all drivers are assumed to be available whenever in the neighborhood, and we emphasized the importance of defining *availability* from a socio-technical system perspective.

Conceptualization of vehicle-to-grid contracts

To cope with the different needs and preferences from the actor and system perspective, we proposed three contract types for V2G based on the literature on V2G and on demand-side response: price-based (PBC), volume-based (VBC) and control-based contracts (CBC). In each of them, the rules for availability and the boundary conditions were defined differently. Therefore, they can be used to engage prosumers with a range of needs within systems with different characteristics and goals. For each contract type, we defined a different combination of rules.

With price-based contracts, drivers can define the minimum price they want for the car to be used for V2G services. Their vehicle is available for V2G for the time the vehicle is plugged in and until the guaranteed minimum fuel level is reached. Therefore, once they plug-in the energy available is defined by the fuel at plug in and the guaranteed level. The remuneration is based on the set minimum price.

With volume-based contracts, drivers commit to having a certain amount of energy available during a given time interval. This means that they have to be plugged in during that time, and after the agreed time, even if plugged in the car is not available to the aggregator. If the committed volume has been used by the aggregator, the car is not available even if it is within the time interval. In this case, the aggregator will activate V2G based on the system's need. Because of the commitment of energy and time, the aggregator may provide a capacity payment next to the remuneration for V2G supplied.

Finally, with control-based contracts, drivers are available while they are plugged in, similarly to the price-based contracts. The amount of energy available also depends on the fuel at plug-in and the guaranteed fuel level. In this case, V2G is activated based on system's needs. While there is no commitment, capacity payments can be used to reward availability.

Performance of vehicle-to-grid contracts

Vehicle-to-grid contracts in a microgrid

The effect of these contracts was investigated in two agent-based models of different Car as Power Plant systems. First, we built an agent-based model of the Car as Power Plant microgrid. We focused on the role of volume-based and control-based contracts in the system, since the goal was to balance the local energy supply and demand. Both the electricity price in the system and the V2G remuneration were defined with a capacity and an energy payment. Although control-based contracts have no energy commitment, a minimum fuel level for plug-in was introduced. This was to avoid allowing vehicles to plug-in when they have no fuel. With this model, different contract implementation strategies for each contract type were compared. With a top-down seasonal contract, the plug-in requirements or time and volume commitment from the vehicles was high in the winter and reduced in the summer months. In a more bottom up implementation, we compared the flexible VBC and fixed CBC implementations. In both simulations, driver agents adjusted their participation each month, based on their individual performance with respect to the average performance.

The system performance was analyzed in a multi-criteria assessment. To compare the performance from a socio-technical perspective we identified indicators corresponding to reliability, economic, and driver autonomy criteria. The results showed that control-based seasonal contracts have the highest reliability and economic performances and the lowest autonomy performance. On the other hand, volume-based flexible contracts allow the highest level of autonomy to drivers, while performing lowest in terms of system reliability and economic performance. This changed, however, when the criteria were evaluated differently. Due to the high profit level, control-based seasonal contracts led to highest performance for drivers, and lowest performance for the rest of the system. This showed how different types of rules affect the operation of the system. The way in which the system is evaluated eventually depends on the actors involved in its design process. Knowing the interests of all actors can help make decisions about the goal of the system, the type of contract needed and how it can be implemented.

Vehicle-to-grid contracts for wholesale market participation

A second agent-based model was built to explore the use of price-based contracts in a Car-Park Power Plant. We explored the role of price-based contracts in the participation of FCEVs in wholesale electricity markets with high solar and wind energy penetration. The modeled system was a car park with on-site hydrogen production from local PV and electricity from the wholesale market. The agents were FCEV drivers that use the car park either for 'Home' or 'Work'-hour parking. For this case, the remuneration structure was defined as the contractual minimum price accepted by the driver plus a profit margin. This additional income was calculated from the difference between market price and the driver's minimum price, which is shared between the driver and the aggregator as a function of the fuel availability when plugging in. We analyzed the effect of this contract type on the Car-Park Power Plant and the actors' performances in three energy and policy scenarios: 80% solar and wind capacity with low, medium, high carbon allowance prices. Further, two dispatch rules used by the aggregator in the car park were considered: fuel and start-up. With the first one, the aggregator switches on vehicles in descending order of fuel availability. With the start-up dispatch rule, the aggregator switches on vehicles in ascending order of total fuel cell start-ups. Driver agents evaluated their performance with respect to other drivers with the same parking profile. When it was below average, driver agents tried to improve their performance by either increasing their refilling needs or by reducing the guaranteed fuel level contract parameter.

The relationship between profit level and some driver characteristics was analyzed, namely the parking profile, arrival time, and parking duration. Using Latent Class Analysis, two five-cluster models were determined. Results showed that while the parking duration seems to be the most important indicator of profit potential, the arrival time also defines the opportunities for V2G. With a limited number of plug-in points, some vehicles may often arrive when there are no dischargers available. Moreover, the availability of other cars also influences the profit potential, as V2G can only be dispatched in units of 100kWh. Therefore, these results showed additional interdependencies when evaluating the profit potential of V2G in electricity markets.

Conclusions

This thesis provides knowledge on how to leverage the power from FCEVs using contracts that define the rules on availability and boundary conditions for vehicle-to-grid operation. The simulation experiments bring to light additional rules to be considered within the contracts and higher level institutions that could be further explored. The simulation of Car as Power Plant systems in agent-based models has demonstrated the suitability of this modeling and simulation approach in incorporating aspects from the physical system, the actor network, and the institutions, especially at the operational level. From a scientific point of view, this thesis contributes to the study of innovative energy technologies with an operational and socio-technical system perspective. It demonstrated the importance of new institutions needed to bring innovative technologies into being.

Samenvatting

Introductie

In de transitie naar koolstofarme energiesystemen, vraagt de groei van verschillende hernieuwbare energiebronnen (V-RES) zoals de zon en de wind naar meer flexibele maatregelen. Deze zijn nodig om beter om te gaan met de toegenomen onzekerheid en de variabiliteit die van invloed is op de resterende vraag. Traditionele spelers in de sector kunnen deze flexibiliteit aanbieden via aan/uitschakelbare energiebronnen, opslag, vraagrespons en verhoogde interconnectie. Er zijn echter ook steeds meer mogelijkheden voor nieuwe actoren en rollen. Aggregatoren kunnen bijvoorbeeld de flexibiliteit van kleine consumenten benutten en namens hen verhandelen op de elektriciteitsmarkten. Deze flexibiliteit kan ook worden aangeboden vanuit andere sectoren, zoals verwarming en transport. Met de toepassing en verspreiding van elektrische voertuigen wordt de geaggregeerde capaciteit hiervan geacht een aanzienlijk potentieel te hebben ter ondersteuning van het elektriciteitsnet in de toekomst. Voertuigen worden slechts 5% van de tijd gebruikt om in te rijden. Dus wanneer ze geparkeerd stilstaan, kunnen ze worden gebruikt voor het bieden van flexibiliteit, bijvoorbeeld als opslag of voorziening van *'vehicle-to-grid'* (V2G) energie.

Het *Car as Power Plant* (CaPP) concept biedt geïntegreerde energie en transportsystemen op basis van hernieuwbare energie en brandstofcelauto's (FCEVs). In dit concept wordt waterstof gebruikt voor opslag van hernieuwbare elektriciteit, transport en herelektrificatie. FCEVs die geparkeerd staan kunnen namelijk worden gebruikt om flexibele elektriciteit te leveren via V2G. In deze context worden voertuigeigenaars en bestuurders prosumenten in het elektriciteitssysteem. Vanuit het oogpunt van een sociotechnisch systeem, wordt de beschikbaarheid van FCEVs voor V2G niet alleen beperkt door de rijdynamiek van de bestuurder maar ook door zijn bereidheid om deel te nemen. Prosumenten, met hun verschillende acties en participatie voorkeuren, moeten worden overwogen bij het analyseren van de haalbaarheid van het V2G concept. Wat nog belangrijker is, is het definiëren van de regels die nodig zijn voor het beheer van V2G transacties. Dit proefschrift onderzocht de werking van brandstofcelauto's voor V2G in CaPP systemen vanuit het oogpunt van een socio-technisch systeem. De belangrijkste onderzoeksvraag was *"Hoe kunnen FCEVs van prosumenten ingezet worden als bronnen van flexibiliteit in CaPP systemen?"*. Deze vraag was beantwoord vanuit vier verschillende perspectieven: 1) Rol van instituties in de uitvoering van V2G, 2) Implicaties van V2G participatie, 3) Conceptualisatie van V2G contracten, en 4) Prestaties van V2G contracten.

Rol van instituties in de uitvoering van V2G

Instituties worden gedefinieerd als de regels die structuur geven aan sociale interacties. In dit onderzoek hebben we de instituties geclassificeerd volgens het vier-lagen institutie model van Williamson. In het literatuuronderzoek hebben we de rol van instituties in de implementatie van V2G onderzocht door de literatuur te analyseren die zich richten op één of meer institutionele lagen. De onderwerpen in de literatuur werden ingedeeld in drie categorieën: 1) Technisch-economische beoordelingen, 2) V2G contracten, en 3) Institutionele omgeving. De drie institutionele perspectieven toonden de rol van instituties bij V2G implementatie vanuit verschillende tijdschalen en perspectieven. Op de operationele tijdschaal is het beheer van V2G transacties verkend met het gebruik van contracten. We ontdekten dat interacties tussen contracten, de fysieke systeemwerking en het gedrag van actoren niet is onderzocht in de literatuur. Over het algemeen komt het socio-technische systeemperspectief zeldzaam voor in de literatuur, mede omdat de kenmerken en het gedrag van actoren niet worden besproken. Dit proefschrift heeft uitgebreid de rol van contracten onderzocht in de werking van CaPP systemen vanuit een socio-technisch systeemperspectief.

Implicaties van V2G participatie

Om de implicaties van V2G voor bestuurders beter te begrijpen hebben we de werking van het fysieke systeem van een CaPP microgrid onderzocht. De beschikbaarheid van voertuigen voor V2G werd gedefinieerd door het rijschema van elke auto, dat was afgeleid van mobiliteitsgegevens uit de echte wereld. Zo werd aangenomen dat auto's beschikbaar zijn als ze in de buurt waren. Rijschema's bepaalden ook de veranderende niveaus van brandstof en de minimale brandstofbehoeften om te rijden. De resultaten toonden dat voertuigen gemiddeld 50% van de tijd beschikbaar waren en dat elk voertuig slechts een vijfde van die tijd werden gebruikt. De 'capaciteitsfactor' van brandstofcelvoertuigen toonde echter seizoensgebonden fluctuaties, net als de resterende energievraag. De resultaten benadrukten het belang van de beschikbaarheid van voertuigen in systemen waarbij FCEVs worden gebruikt voor betrouwbaarheidsdoeleinden. Bovendien werd de conclusie getrokken dat het autonomieverlies hoog is wanneer wordt aangenomen dat alle bestuurders beschikbaar zijn als ze in de buurt zijn en we benadrukten het belang van het definiëren van de beschikbaarheid vanuit een socio-technisch systeemperspectief.

Conceptualisatie van V2G contracten

Om te voldoen aan de verschillende behoeften en voorkeuren van het actoren en systeemperspectief, hebben we drie contracttypen besproken op basis van de literatuur over V2G en vraagrespons: *price-based* (PBC), *volume-based* (VBC) en *control-based contracts* (CBC). In elk van deze contracten zijn de regels voor beschikbaarheid en de grensvoorwaarden anders gedefinieerd. Daardoor kunnen ze gebruikt worden om prosumenten met een reeks aan behoeften te bereiken in een systeem met verschillende kenmerken en doelen. Voor elk type contract hebben we een verschillende combinatie van regels gedefinieerd.

Bij *price-based contracts* kunnen bestuurders de minimumprijs bepalen die ze willen ontvangen om van hun voertuig gebruik te mogen maken voor V2G diensten. Hun voertuig is beschikbaar voor V2G gedurende de tijd dat het voertuig is aangesloten totdat het gegarandeerde minimum brandstofniveau is bereikt. Dus zodra het voertuig is aangesloten, wordt de hoeveelheid beschikbare energie gedefinieerd door de brandstof bij aansluiting en het gegarandeerd niveau. De vergoeding is gebaseerd op de vastgestelde minimumprijs.

Bij *volume-based contracts*, verplichten bestuurders zichzelf om een bepaalde hoeveelheid energie beschikbaar te houden gedurende een bepaald tijdsinterval. Dit betekent dat ze aangesloten moeten zijn gedurende deze tijd en dat het voertuig niet beschikbaar is voor de aggregator na de afgesproken tijd, zelfs als het aangesloten is. Als het toegewezen volume is gebruikt door de aggregator, is het voertuig niet beschikbaar, zelfs als dit binnen het tijdsinterval is. In dit geval wordt V2G geactiveerd door de aggregator op basis van de behoeften van het systeem. Vanwege de toewijding van energie en tijd, kan de aggregator naast de vergoeding voor V2G een capaciteitsvergoeding bieden. Tenslotte zijn er de *control-based contracts*, waarbij de bestuurders beschikbaar zijn terwijl ze zijn aangesloten. Dit is vergelijkbaar met de *price-based contracts*. De hoeveelheid energie dat beschikbaar is, is ook afhankelijk van de brandstof bij aansluiting en het gegarandeerde brandstofniveau. In dit geval wordt V2G geactiveerd op basis van de behoeften van het systeem. Hoewel er geen verplichting is, kunnen capaciteitsvergoedingen worden gebruik om de beschikbaarheid te belonen.

Prestaties van V2G contracten

V2G contracten in een microgrid

Het effect van deze contracten is onderzocht met behulp van twee agent-gebaseerde modellen van verschillende CaPP systemen. Eerst hebben we een agent-gebaseerd model van het CaPP *microgrid* gebouwd. Om de lokale energievoorziening en -vraag in evenwicht te houden, hebben we ons gericht op de rol van *volume-based* en *control-based contracts* in het systeem. Zowel de elektriciteitsprijs in het systeem als de V2G vergoeding werden gedefinieerd met een capaciteitsvergoeding en een energievergoeding. Hoewel *control-based contracts* geen energie verplichting hebben, is er een minimum brandstofniveau voor plug-in geïntroduceerd. Dit was om te voorkomen dat voertuigen werden toegestaan om aan te sluiten als ze geen brandstof hebben. Verschillende strategieën voor de implementatie van elk type contract werden vergeleken met dit model. Met een top-down seizoenscontract waren de plug-in vereisten of tijd- en volumetoezeggingen van de voertuigen hoog in de winter en lager in de zomermaanden. In het geval van een bottom-up implementatie, hebben we de flexibele VBC vergeleken met de vaste CBC implementaties. In beide simulaties pasten de bestuurders hun deelname maandelijks aan, op basis van hun individuele prestaties in verhouding tot de gemiddelde prestatie.

De systeemprestaties zijn geëvalueerd met behulp van een multi-criteria analyse. Om de prestaties te vergelijken vanuit een socio-technisch perspectief, hebben we indicatoren geïdentificeerd die overeenkomen met criteria voor betrouwbaarheid, economie en de autonomie van bestuurders. De resultaten toonden aan dat seizoensgebonden *control-based contracts* de hoogste prestaties hebben voor betrouwbaarheid en economie en de laagste autonomie prestatie. Flexibele *volume-based contracts* daarentegen bieden de hoogste prestaties voor autonomie en de laagste prestaties voor betrouwbaarheid en economie. Dit veranderde echter wanneer de criteria anders werden beoordeeld. Vanwege het hoge winstniveau, hebben seizoensgebonden *control-based contracts* geleid tot de hoogste prestaties voor bestuurders en de laagste prestaties voor de rest van het systeem. Hieruit bleek hoe verschillende soorten regels van invloed zijn op de werking van het systeem. De manier waarop het systeem wordt geëvalueerd, hangt uiteindelijk af van de actoren die betrokken zijn bij het ontwerpproces. Het kennen van de belangen van alle actoren kan helpen bij het beslissingsproces over het doel van het systeem, het type contract dat nodig is en hoe het kan worden geïmplementeerd.

V2G contracten voor deelname aan groothandelsmarkt

Een tweede agent-gebaseerd model werd gebouwd om het gebruik van *price-based contracts* te onderzoeken in een *Car-Park Power Plant* (CPPP). We hebben de rol van *price-based contracts* bij FCEVs onderzocht met betrekking tot hun deelname in groothandelsmarkten voor elektriciteit met een hoge penetratie van zonne- en windenergie. Het gemodelleerde systeem was een parkeerterrein met on-site waterstofproductie van lokale PV en elektriciteit van de groothandelsmarkt. De agenten waren FCEV bestuurders die het parkeerterrein gebruiken voor thuis of werk op een uur-basis. In dit geval werd de vergoedingenstructuur gedefinieerd als de contractuele minimumprijs die door de bestuurder wordt geaccepteerd plus een winstmarge. Dit extra inkomen is berekend op basis van het verschil tussen de marktprijs en de minimumprijs van de bestuurder, dat vervolgens wordt verdeeld onder de bestuurder en de aggregator, afhankelijk van de beschikbaarheid van brandstof bij het aansluiten. We hebben het effect van dit type contract op het Car-Park Power Plant en de prestaties van de actoren onderzocht in drie verschillende energie- en beleidsscenario's: 80% zon- en windcapaciteit met lage, gemiddelde en hoge prijzen op de emissierechten van CO2. Daarnaast zijn er ook twee dispatch regels meegenomen die worden gebruikt door de aggregator op het parkeerterrein: brandstof en start-up. Bij de eerste regel schakelt de aggregator voertuigen in, in aflopende volgorde op basis van de beschikbaarheid van brandstof. Bij de start-up regel, schakelt de aggregator in oplopende volgorde voertuigen in op basis van het totale aantal 'start-ups' van de brandstofcel. Bestuurders evalueren vervolgens hun prestaties in verhouding tot andere bestuurders met dezelfde parkeer profiel. Wanneer de prestaties onder het gemiddeld niveau waren, probeerden de bestuurders hun prestaties te verbeteren door het verhogen van hun bijvulbehoeften of door het verlagen van de contract parameter van het gegarandeerde brandstofniveau.

De relatie tussen het winstniveau en bepaalde kenmerken van de bestuurder, namelijk het parkeer profiel, de aankomsttijd en de parkeerduur, werd geanalyseerd. Met behulp van Latent-Class Analyse werden twee vijfclustermodellen bepaald. De resultaten toonden aan dat terwijl de parkeerduur de belangrijkste indicator is voor het winstpotentieel, de aankomsttijd ook de kansen bepaalt voor V2G. Door een beperkt aantal plug-in punten kunnen sommige voertuigen vaak op een tijdstip aankomen wanneer er geen ontlaadmachines beschikbaar zijn. Bovendien heeft de beschikbaarheid van andere auto's ook invloed op het winstpotentieel, aangezien V2G alleen ontladen kan worden in eenheden van 100kWh. Zodoende toonden deze resultaten extra onderlinge afhankelijkheden bij het evalueren van het winstpotentieel van V2G op de elektriciteitsmarkten.

Conclusies

Dit proefschrift biedt kennis over hoe de kracht van FCEVs benut kan worden met behulp van contracten die de regels voor beschikbaarheid en grensvoorwaarden definiëren voor de werking van V2G. De simulatie-experimenten hebben aangetoond dat aanvullende regels overwogen moeten worden met betrekking tot de contracten en dat nader onderzoek gedaan moet worden naar instituties op hoger niveau. De simulatie van CaPP systemen in agent-gebaseerde modellen heeft aangetoond dat deze modellerings- en simulatiebenadering geschikt is voor het analyseren van verschillende aspecten van het fysieke systeem, het netwerk van actoren en de instituties op een operationeel niveau. Vanuit een wetenschappelijk oogpunt draagt dit proefschrift bij aan kennis over innovatieve energie technologieën vanuit een operationeel en socio-technisch systeemperspectief. Het toont het belang van nieuwe instituties aan voor het uitvoering brengen van innovatieve technologieën.

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Esther H. Park Lee
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1

Introduction

1.1. The European energy transition

1.1.1. Decarbonization in the electricity sector

In an effort to limit climate change, the European Union (2012) has pledged its commitment to *"reducing greenhouse gas emissions to 80-95% below 1990 levels by 2050"*. One of the main approaches to achieve the decarbonization goals is by supporting the increased use of renewable energy across different sectors. The European Union and IRENA (2018) emphasize the large potential of increasing renewable energy cost-effectively in all EU countries, and recognize that reaching a 34% share of renewable sources in the energy mix in 2030 would be feasible. The growth of renewable energy in the electricity sector has been especially significant, since 2005 (European Environment Agency, 2017). In 2016, almost 90% of the new capacity for electricity generation in Europe consisted of renewable sources, a trend consistent with the preceding nine years. According to projections of the European Union and IRENA (2018) by 2030, the installed capacity of wind and solar photovoltaic (PV) power generation, both variable renewable sources, could grow to 327 gigawatts and 270 gigawatts, respectively. Other renewable energy technologies including biomass, geothermal, and hydropower are projected to reach 23 gigawatts.

1.1.2. Flexibility needs

The growth of variable renewable electricity sources (V-RES), however, is increasing the demand for flexibility in power systems across Europe (European Union & IRENA, 2018). As Figure 1.1 shows, the variability in demand, generation, and possible outages has to be addressed by using flexibility sources: dispatchable generation, demand side management, storage and interconnection (Holttinen et al., 2013). Such sources already exist in the electricity sector (Ecofys, 2014). Conventional generation technologies, such as gas turbines and internal combustion engines, are being used for this purpose due to their techno-economic characteristics. Renewable dispatchable electricity sources, for example from biogas plants, can also be used to provide flexibility.

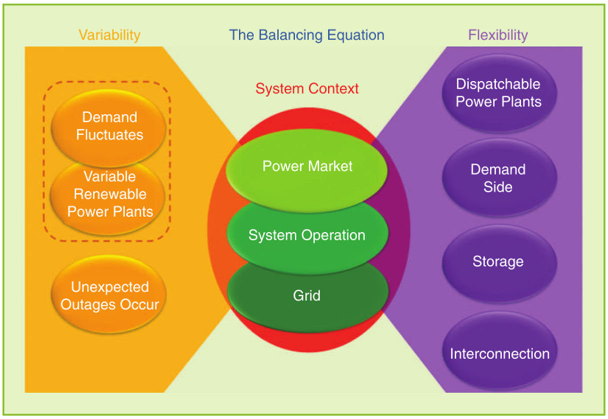

Figure 1.1: Flexibility needs, sources and enablers. *Source: (Holttinen et al., 2013)*

While the power from non-dispatchable, variable renewable energy sources like solar PV and wind can be curtailed when needed, in the presence of subsidies there is no incentive for producers to do so. In the demand side, industrial consumers can vary their consumption patterns with low costs depending on their processes. There are also several storage options, such as pumped hydro storage, flywheels, batteries and power-to-gas. Moreover, liberalized electricity markets are designed to enable the use of flexibility sources cost-efficiently. Balancing markets, in particular, allow the system to adapt to differences in the system's supply and demand in the short-term. With the increase of V-RES penetration in electricity systems, however, the interest in intraday markets is also growing.

Flexibility needs can also be met by actors that used to have the role of consumers in the traditional electricity supply chain, from big industrial consumers to businesses and households. With the transition to smart grids, active participation of consumers especially in low-voltage grids is gaining more attention (USEF Foundation, 2017). For some years, commercial and residential consumers have been taking the role of *prosumers* by feeding electricity into the grid using distributed generation technologies like rooftop solar PV. However, prosumers can also offer flexibility services by better adjusting their demand to the supply, through demand-side management schemes and incentives (Koliou, 2016). As discussed in the EU Winter Package, the role of prosumers is set to increase in future clean energy systems (European Commission, 2016). Initiatives for local solutions, such as community energy systems, further point out the importance of prosumers and distributed energy sources in the future (Koirala, 2017). Furthermore, electrification trends, seen in the increasing adoption of heat pumps and electric vehicles (European Union & IRENA, 2018) indicate that the overall demand for electricity will continue to grow. These technologies can also be used to increase demand-side flexibility (Energie Koplopers, 2016; USEF Foundation, 2015).

1.1.3. Sector coupling and electric mobility

As a result of the changing needs in the energy transition and the electrification trends in different energy end-use sectors, system integration or sector coupling can have a significant role in increasing flexibility and reaching decarbonization goals (European Union, 2018; IRENA, IEA, & REN21, 2018). As the second biggest end-use sector and with its electrification trends, the transport sector has the potential to provide flexibility in the electricity systems by engaging individual consumers. Alternative fuel vehicles that provide cleaner options for mobility include flexifuel vehicles and electric drive vehicles (EDVs) such as battery electric, hybrid, and fuel cell electric vehicles. While niche developments in electric mobility started around two decades ago, they have been seeing a new momentum since 2005 (Dijk, Orsato, & Kemp, 2013).

Battery electric vehicles (BEVs) are all-electric vehicles that have an electric motor, a controller and a battery that stores electricity. BEVs are charged from the grid. Regenerative braking is also used to store extra energy. The increasing adoption of this type of vehicle has an impact on electricity systems, as they represent an added load. *Hybrid electric vehicles* consist of both a conventional ICE and an electric propulsion system. There are different configurations and degrees of hybridization, but the two main types are the gasoline-electric hybrid vehicle (HEV) and the *plug-in hybrid vehicle* (PHEV). The first type has a small electric motor and has one fuel source, gasoline. The small battery is recharged via regenerative braking, but it cannot be charged from the grid. PHEVs, on the other hand, have a bigger electrical motor and battery, and can either use gasoline or charge its battery by connecting the car to the grid. In this case, only PHEVs have an impact on the electricity system.

Fuel cell electric vehicles (FCEVs), also known as fuel cell vehicles (FCVs) are also all-electric vehicles that have an electric propulsion system. Instead of storing energy in a battery, FCEVs rely on a gaseous fuel that is converted to electricity using a fuel cell stack. Currently, the commercialized FCEVs run on hydrogen. While FCEVs are also electric vehicles, they do not increase the load of the electricity system. Instead, the gas tanks in the FCEVs can be refilled at hydrogen tanking stations.

Table 1.1 shows the role of different EDV types in the transport sector and in future integrated transport and electricity systems. As indicated above, BEVs and PHEVs represent an added load, while FCEVs do not. When integrating the transport and electricity systems, BEVs, PHEVs and FCEVs can provide some form of flexibility. Although FCEVs are all-electric just as BEVs, they are often considered a rival technology and their characteristics are often compared Thomas (2009) due to the different power source and storage system they have and the infrastructure they rely on.

Table 1.1: Role of electric drive vehicles with and without sector coupling

Type	No sector coupling	Integrated transport and electricity systems
BEV	Variable demand	Demand side response, storage, flexible generation
HEV	None	None
PHEV	Variable demand	Demand side response, storage, flexible generation (to a lesser extent)
FCEV	None	Flexible generation

The use of plug-in EVs[1] to provide flexibility has been extensively studied (Flath, 2013; Mwasilu, Justo, Kim, Do, & Jung, 2014; Verzijlbergh, 2013). Through smart charging, electric vehicles can delay electricity consumption following system needs or prices. Since vehicles can be charged when there is surplus renewable energy in the system, they can also be considered distributed storage devices. Moreover, the energy in these vehicles can also be fed back to the grid. Through vehicle-to-grid (V2G), aggregated electric vehicles can supply power when needed (Kempton & Tomić, 2005a, 2005b). Vehicles are considered to be parked about 96% of the time (Kempton & Letendre, 1997), and therefore they can be used as flexibility sources - decreasing the need to use costly thermal power plants for peak power supply and balancing purposes.

Kempton and Tomić (2005a) discuss the suitability of different EVs for different V2G services. While the supply of baseload power is not deemed competitive for any type of EDV, peak power can be profitable under certain circumstances. Ancillary services such as spinning reserves and regulation (up) can be interesting for EDVs, given the short periods of supply and the fast response needed. While FCEVs are considered more suitable for spinning reserves, BEVs are more suitable for regulation services. This is further discussed in the literature review.

1.2. The Car as Power Plant

1.2.1. Concepts

In line with these developments, the Car as Power Plant (CaPP) concept has been proposed as a flexible integrated transport and electricity system that is clean, efficient, flexible, reliable and affordable (van Wijk & Verhoef, 2014). This concept delves into the potential role of hydrogen in future electricity systems, which is increasingly being recognized as the 'missing link' for further integrating renewable energy sources in Europe. With the use of hydrogen and FCEVs, this concept explores additional opportunities for sector coupling through the use of different energy carriers (Olczak & Piebalgs, 2018). Using electrolyzers, hydrogen can be produced from renewable electricity, allowing it to be stored in the medium and long term. The use of this type of 'green' hydrogen in FCEVs would contribute to the decarbonization of the transport sector. Moreover, parked FCEVs can be used as flexible power sources through vehicle-to-grid, allowing the re-electrification of green hydrogen. Therefore, the CaPP concept combines renewable energy with two types of flexibility sources: storage and dispatchable power.

The CaPP concept can be applied in different ways. The *Car as Power Plant microgrid*, for example, proposes a microgrid that provides locally generated electricity to residential consumers. It consists of local renewable generation, hydrogen production and vehicle-to-grid with FCEVs owned by the residents. A CaPP smart city concept can also be developed, at a bigger scale, to include commercial consumers and a larger number of residents. In both cases, hydrogen and vehicle-to-grid can increase the self sufficiency of the system: firstly, by storing renewable electricity in the form of hydrogen, and secondly, by using this hydrogen in FCEVs for meeting the local residual demand as well as for driving. Another example is the *Car-Park Power Plant*, a car park in which

[1] In this thesis, the term "plug-in EV"/"EV" will be used to refer to BEVs and PHEVs.

aggregated FCEVs are used as a virtual power plant (VPP). When green hydrogen is used by the FCEVs, the Car-Park Power Plant can provide flexible clean energy to the grid. Local hydrogen production and refilling also allows the system to provide flexibility to the larger electricity system through its storage capacity.

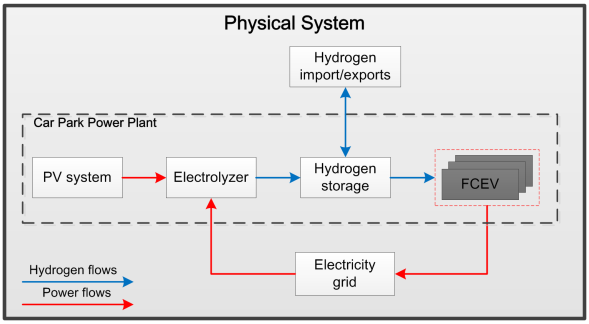

Figure 1.2: Car-Park Power Plant

Figure 1.2 depicts the physical flows in a Car-Park Power Plant. In Oldenbroek et al. (2017) the authors present the specific energy consumption and production values (HHV [2] basis) expected in the Near Future (2020) and Mid Century (2050) scenarios. Based on technology forecast studies, the calculated specific energy consumption values for the electrolyzer (electricity → hydrogen) are 53.4 kWh/kg and 45.8 kWh/kg for 2020 and 2050. For the FCEVs (hydrogen → electricity), the specific energy production values are 20.3 kWh/kg and 23.6kWh/kg.

The combination of energy carriers in the CPPP reflects possible synergies between the hydrogen and electricity networks, and between the power and transport sectors. This concept is envisioned for the future and is based on the possibility of embedding new technologies and energy practices in current systems. As such, its success depends on many developments across the electricity and road transport sectors. To explore its feasibility, CaPP systems can be designed and analyzed from different perspectives. Each approach can provide distinct insights, thus improving our understanding of them and enriching the design and development process (Farahani et al., 2019).

Techno-economic approaches can be used to investigate whether CaPP systems can be designed as clean, efficient, flexible, reliable and affordable systems. A study of a CaPP smart city for an average European city shows how this system can be designed cost-effectively in the near future and in 2050 (Oldenbroek et al., 2017). This approach helps understand under what techno-economic conditions these systems can be designed to fulfill their purpose. With the system design, its operation and performance can also be analyzed from a techno-economic perspective. Moreover, the uncertainties in the prediction of demand, renewable energy supply and vehicle availability can be addressed with model predictive control algorithms. These can provide insights on how to operate each system component optimally, given the uncertainties at hand (Alavi, Park Lee, van de Wouw, De Schutter, & Lukszo, 2017).

[2] Higher Heating Value = 39.4 kWh/kg

Even when designed optimally, the actual operation of CaPP systems depends on the participation of FCEV drivers as prosumers. The concept of vehicle-to-grid was based initially on the assumption that cars are parked 96% of the time (Kempton & Letendre, 1997). While a single car may not be continuously available, it was assumed that the availability of a large number of vehicles would be *"highly predictable"* (Letendre & Kempton, 2002). This assumption implies that drivers would always be plugged in to the grid while parked and would be willing to allow the use of their vehicle to support the grid. However, this assumption can be disputed, especially in the case of FCEVs, which do not use electricity *from* the grid. To participate in V2G, drivers would have to make a conscious decision to plug-in, which is not a habit that comes with daily FCEV use. The feasibility of vehicle-to-grid with any type of electric drive vehicle depends on whether drivers want to participate, and to what extent.

1.2.2. Socio-technical system perspective

Beyond the physical system

Car as Power Plant systems can be described more comprehensively from a socio-technical perspective, that is, by considering them as a combination of physical and social systems. The first includes technical artefacts and physical flows and processes, as shown in Fig. 1.2. The social system includes the actors involved and their behavior and interactions, which are governed by institutions. The combination of the two, as shown in Fig. 1.3 helps understand how the physical processes related to vehicle-to-grid are influenced by actions and decisions made by actors in the social system, and vice versa. In this view, the operation of FCEVs for vehicle-to-grid increases the complexity of the system. In this research, we consider fuel cell vehicles as artefacts that are owned and used by individual drivers, and their participation as prosumers involves an innovative energy practice. Moreover, the operation of individual fuel cell vehicles depends on the decisions of the aggregator, the actor that participates in the market on behalf of the drivers, who become prosumers in the system. Therefore, the integration of vehicle-to-grid in electricity systems involves new roles and new interactions, both social and physical.

New roles, new rules

The participation of new actors and their interactions in the supply of V2G also involves new institutions, which can be defined as *"durable systems of established and embedded social rules that structure social interactions"* (Hodgson, 2006). To leverage the power of electric vehicles, new rules are needed to define actions and interactions that can deeply affect the system operation. As depicted in Fig. 1.3, rules and responsibilities regarding the use of FCEVs for vehicle-to-grid have to be agreed upon between the aggregator and the drivers. These would include the conditions under which the aggregator is allowed to use the FCEVs, the required actions by drivers, and the remuneration. When analyzing the Car as Power Plant from a socio-technical system perspective, the feasibility of using FCEVs as power plants will be influenced by the institutions that guide the new interactions.

As mentioned in the previous section, the European energy transition envisages an increasing role of prosumers and new sources of flexibility. To understand how future

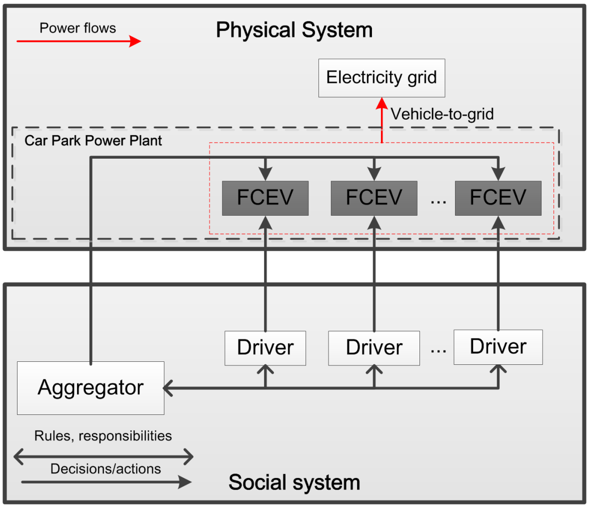

Figure 1.3: Relationships of actors in V2G supply

sustainable energy systems can be designed and developed, a socio-technical systems view helps in recognizing the complexities that need to be addressed (Moncada, Park Lee, Okur, Chakraborty, & Lukszo, 2017). Technical and techno-economic perspectives provide a wealth of knowledge about the feasibility and optimal operation of innovative technologies and systems. However, a socio-technical system perspective can address more specifically the role of the actors in such systems and provide further insights on how they can be developed.

1.3. Research goal and questions

The goal of this research is to explore the operation of FCEVs as power plants in Car as Power Plant systems, from a socio-technical systems perspective. The main research question is:

How can prosumers' FCEVs be leveraged as flexibility sources within Car as Power Plant systems?

The research sub-questions addressed in this thesis are:

1. *What roles do institutions play in vehicle-to-grid implementation?*
2. *What are the operational implications of vehicle-to-grid participation for individual vehicles and for the system as a whole?*
3. *What rules can be used to manage vehicle-to-grid in Car as Power Plant systems?*
4. *How do different contract types and rules affect the operation of vehicle-to-grid in Car as Power Plant systems?*

To answer these sub-questions we first analyze literature related to the institutional aspects of vehicle-to-grid, comparing to what extent the physical and social systems are considered. Then, we explore the operation of FCEVs in a CaPP system from a technical perspective to draw conclusions on how the physical system operation affects the involved actors. We quantify the implications of V2G operation for drivers by modeling the use of individual vehicles in the system.

To explore the rules that can be used to manage FCEVs as power plants in CaPP systems, we define the main set of rules necessary in a V2G contract. Drawing lessons from vehicle-to-grid and demand-side management literature, we propose three contract types for vehicle-to-grid that involve different sets of rules. Then, we explore the effect of these contracts in CaPP systems with different purposes and characteristics. To do this, we build two agent-based models in which we formalize vehicle-to-grid contracts and also address additional questions about operational strategies. The effect of the contracts and aggregator strategies in Car as Power Plant systems is quantified by using the models in simulation experiments. Our approach is detailed in the next chapter.

1.4. Scope

1.4.1. Scientific relevance and contribution

This thesis provides a multi-disciplinary approach to studying the feasibility of prosumer-centered innovative systems, based on a socio-technical systems perspective. More specifically, there is a strong focus on the role of new institutions needed at the operational level to better understand how innovative technologies or systems can be implemented. The formalization of institutions in operational agent-based models provides a quantitative approach for testing and exploring the influence of certain social rules on the system performance. The combination of decisions, actions, physical flows, and rules in operational agent-based models provides a more comprehensive view of what is needed to operate innovative systems. As such, this thesis can encourage the use of this approach to explore energy topics beyond the Car as Power Plant and vehicle-to-grid. Moreover, operational agent-based models can be combined with exploratory models that address long-term development questions regarding the energy transition in Europe. Therefore, the contribution of this thesis is two-fold:

Research of technologies supporting the energy transition This research contributes to the research of innovative energy technologies and systems supporting the energy transition, by providing a different approach to analyze their feasibility. The use of a socio-technical system operation framework helps address the innovation at the system level and can be used to analyze how the physical system, actors and institutions interact at the operational level. Through the use of agent-based models we show how all these concepts can be formalized to explore these interactions.

Vehicle-to-grid research This thesis also contributes to the research of vehicle-to-grid implementation, with the conceptualization and formalization of V2G contract types. Contract parameters represent the responsibilities and conditions for vehicle-to-grid operation as well as possible remuneration structures. Three sets of rules are proposed to engage drivers with heterogeneous needs and preferences in different types of vehicle-to-grid supply. Their formalization in agent-based models allows to make a direct link between driver behavior, physical system operation, and contract parameters. The profitability of vehicle-to-grid for heterogeneous drivers can be analyzed in more detail by taking into account diverse driver characteristics as well as the interdependencies. Ultimately, the lessons learned on the role of contracts in vehicle-to-grid operation can provide insights about its long-term feasibility and the social and institutional conditions for implementation.

1.4.2. Audience

Based on the above, this thesis addresses audiences both in academia and practice. The approach used in this thesis can be of interest for academic researchers with questions about the feasibility of novel technologies in the future. As the implementation of innovations in future systems also depends on their operational feasibility, this research shows how to focus on operation rather than long-term development. More importantly, it demonstrates how to take into account the operations in the physical system, together with the actors' actions and the institutions needed. Exploring these aspects in agent-based models allows to explicitly address them together and helps understand the complexities that are overlooked in purely technical or techno-economic approaches.

Secondly, the outcomes of this research can address policy makers' questions regarding the implementation of vehicle-to-grid and the potential of hydrogen in future energy systems. Moreover, the conceptualization and formalization of contracts for vehicle-to-grid also brings to light questions about how hydrogen prices will influence the profitability of vehicle-to-grid with fuel cell cars. Policy makers can use the lessons of this thesis to explore further what is needed to support the implementation of vehicle-to-grid with fuel cell cars in the future.

Finally, this research addresses energy service companies and businesses who want to develop business models based on vehicle-to-grid. The contracts proposed in this thesis show the different types of agreements that aggregators can use for leveraging FCEVs as flexibility sources. Moreover, they can help energy companies take into account the needs and preferences of prosumers when providing flexibility. Last but not least, the models in this thesis demonstrate how these contracts can be implemented, and explore other relevant implementation and operational strategies to be considered in the process.

1.5. Thesis outline

The rest of this thesis is structured as follows. In Chapter 2 we introduce the theoretical background and approach used in this research. In Chapter 3, we provide a review of the relevant literature, regarding the different approaches for analyzing the feasibility of vehicle-to-grid. In Chapter 4 we explore the operation of a CaPP system with a simulation model. By including the physical system operation and driving needs of heterogeneous vehicles, we analyze the implications for drivers when integrating FCEVs in a local energy system.

Based on the literature review and the analysis of V2G with a socio-technical system perspective, in Chapter 5 we conceptualize three V2G contract types for different systems and driver preferences. These are further formalized in the following two chapters. In Chapter 6 we formalize the volume-based and control-based contracts in an agent-based model of a Car as Power Plant microgrid system. We use the contract parameters to manage the availability and operation of FCEVs. In Chapter 7 we formalize the price-based contract in an agent-based model or the Car-Park Power Plant. In this case, we explore the potential profit of drivers when participating in future wholesale electricity markets with high renewable energy penetration.

Finally, in Chapter 8 we provide a discussion on the research and reflect on the results and the framework used. We finalize with conclusions and recommendations for further research.

2

Theoretical background and research approach

2.1. Introduction

In this chapter we present the conceptual framework and the approach used in this thesis to address the research question: *"How can prosumers' FCEVs be leveraged as flexibility sources within Car as Power Plant systems?"*. First, we introduce the theoretical concepts behind the socio-technical systems view and the role of institutions in socio-technical systems. Then we discuss the chosen modeling approach. Finally, we explain the research approach, which consists of conceptualizing CaPP systems using a socio-technical system operation framework, and then formalizing and exploring them through agent-based modeling and simulation.

2.2. Socio-technical systems view

At the base of our research approach is the concept of *socio-technical systems*: a view that man-made systems like infrastructures, consist of physical/technical elements as well as social elements and actors (Ottens, Franssen, Kroes, & Van De Poel, 2006). Hughes (1989) gives a similar description under the name of *technological systems*. They are formed by physical artifacts as well as organizations, firms, and legislative artefacts – all of which have a role in the functioning of the system as a whole. Carlsson and Stankiewicz (1991) also use the term technological system to refer to a *"network of agents interacting in a specific economic/industrial area under a particular institutional infrastructure"*. However, the term socio-technical system seems more appropriate to refer to their two main components: the physical/technical system and the social system. Flows in the physical system are governed by the rules of physics, whereas the actions and interactions in the social system are governed by social laws: institutions (Ottens et al., 2006; K. Van Dam, 2009). These are not separated, however, as interactions between the two are needed for a system to function: actors make decisions on the operation of the physical system, and the physical system operation has an impact on the functioning of organizations and firms.

Although there is an interest in designing and re-designing socio-technical systems, it is not easy due to their inherent complex nature (De Bruijn & Herder, 2009). Socio-technical systems are composed of many heterogeneous elements interacting with each other in a non-linear way (K. H. Van Dam, Nikolic, & Lukszo, 2013). System interactions lead to emergent behaviors that are difficult to predict, as individual elements act and react to the system (Holland, 1992). Thus, some argue that while components in socio-technical systems can be designed, systems as a whole cannot be designed, as they *"develop through emergence"* (Bots, 2007). In this context, technical design refers to the design of physical processes, technical components, etc. according to the requirements of a system. On the other hand, institutional design may consist of devising rules to reduce uncertainty in social interactions (Koppenjan & Groenewegen, 2005). However, given the inter-relatedness in these systems, any change in one of the components cannot be understood without considering the other (Chappin, 2011). As Scholten and Künneke (2016) argue, a comprehensive design of energy infrastructures consists of the coherence between the physical/technical system and institutional designs. All physical and non-physical artefacts have a role in the operation of a system (Hughes, 1989), and therefore the alignment between technical and institutional designs influences its performance.

2.3. Role of institutions

To investigate the role of institutions in this thesis, we further decompose the social system into the *network of actors* and the *institutions*. While the focus remains on the latter, the actors have to be identified in order to consider their characteristics and actions in the system.

2.3.1. Definitions and classification

Institutions are commonly defined as the *rules of the game* (Bots, 2007; Koppenjan & Groenewegen, 2005; North, 1991), but they can also be described as structures, or systems of rules that structure social interactions (Hodgson, 2006). Goodin (1998) not only limits the definition of institutions to rules and norms but also includes roles and expectations from them. Institutions constrain behavior but also facilitate it by providing the guidelines for interactions (e.g. language or traffic rules). According to Goodin (1998), they have been *"socially constructed"* to provide stability and predictability in social behavior, by reducing uncertainty (Hodgson, 2006; North, 1991). Ostrom (2011) uses the term 'rules' to define actions that are *"required, prohibited, or permitted"*.

A single and widely shared definition of institutions does not exist. There might be a different definition for every discipline, as each one addresses types of rules that exist at distinct levels of social interaction. To that end, Williamson (1998) provides a practical classification through the four layer model. As shown in Fig.2.1, institutions can be classified into four layers or levels. At the highest level are the slow-changing informal norms, beliefs and tacit rules that influence human behavior for centuries.

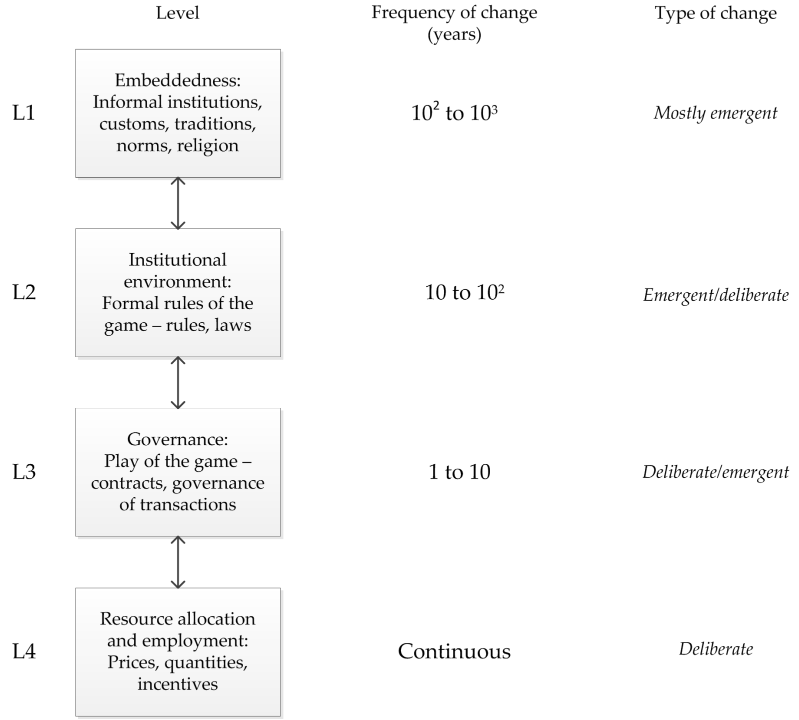

Figure 2.1: Four levels of social analysis. Source: (Williamson, 1998)

These constrain the second level, the more formal rules that include laws, e.g. regarding property rights, and depend on the political environment. In turn, such environment also influences the governance structures and obligations in transactions, e.g. contracts. At the lowest level are the allocation of resources, that is, the prices and quantities that are adjusted frequently as a reaction to the environment. Each level is characterized by a purpose in the social system, a different type and frequency of change, and is explained using different theories.

Layer 1 Informal rules, conventions, and social constraints that *"involve a network of mutual beliefs"* (Hodgson, 2006) among individuals, and are usually not explicit agreements. This layer is usually taken as a given by economists.

Layer 2 Institutional environment, i.e. the formal rules of the game, or first-order economizing (Williamson, 1998). This is the structure within which all kinds of activities are organized, and influences how the system will be operated. This level addresses the economics of property rights – including purchase and sale, as well as the rights of using, changing, receiving profits from its use. Legislation is included, and depends much on the political environment.

Layer 3 Institutions of governance, also known as the play of the game, or second-order economizing (Williamson, 1998). The focus is on the governance structures (markets, firms, etc.), defined with a Transaction Cost Economics (TCE) point of view. Contractual agreements are needed to enforce contracts. Institutions of this type are needed to reduced uncertainty, and the right choice of governance structure will effectively decrease the risks of opportunistic behavior (Williamson, 1998).

Layer 4 It involves marginal conditions (Neo-classical economics/agency theory). Variables like price and output become relevant, as well as the means for efficient incentive alignment taking into account different risk aversion levels. Price and output are adjusted continuously, responding to market conditions.

Institutions at the four layers generally become embedded in social systems in different ways. While informal norms are established and enforced through approval or disapproval by other individuals, formal rules may also involve sanctions (Hodgson, 2006). Even with sanctioning measures, however, rules will only fulfill their purpose when they are widely accepted and obtain a normative status, that is, when they have been accepted and internalized by individuals. As they are shared and repeated, they stabilize behavior. Thus, the acceptance of rules is an important aspect to consider when designing or re-designing institutions. The success of an institutional design will depend on whether (or to what extent) the designed rules are accepted and used by the involved actors. If, for example, a new market for exchanging goods is introduced among a group of individuals, but they ignore the rules of the market and decide to trade using their own rules, the imposed set of rules will not fulfill its intended purpose.

2.3.2. Institutions of governance

To explore the operation of FCEVs as power plants in Car as Power Plant systems, we focus on the actions of actors regarding vehicle-to-grid and the involved economic transaction. Therefore, to learn about the social rules needed at the operational level we focus on the institutions of governance (Layer 3). We use the Transaction Cost Economics (TCE) perspective to consider what type of governing institutions can be used for V2G (Williamson, 1979). In our research, we assume that FCEV drivers in CaPP systems are also the owners. Therefore, regardless of who develops a CaPP system or makes the investments for the other system components, FCEVs are purchased by private owners.

Fig. 2.2 shows the different types of governance, based on the investment characteristics and frequency of transactions. Transactions made with nonspecific investments can be governed with the traditional market governance structure. However, transaction-specific (idiosyncratic) investments are more affected by opportunistic behavior and therefore require neoclassical or relational contracting forms (Williamson, 1979). As indicated in Table 2.1, the characteristics of investments on FCEVs and V2G transactions indicate that bilateral governance (relational contracting) is the appropriate governance form for managing vehicle-to-grid within CaPP systems. Here, *ownership* refers to who has *"control rights and power to exercise control when the contract is incomplete"* (Gui, Diesendorf, & MacGill, 2016). On the other hand,

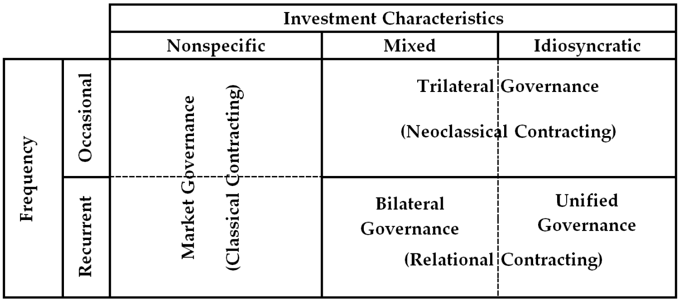

Figure 2.2: Governance structures for different transaction characteristics. Adapted from Williamson (1979)

governance refers to the structure that is used *"to exercise economic and administrative authority through institutions, mechanisms and processes"* (Gui et al., 2016).

Table 2.1: Characteristics of V2G transactions using FCEVs within CaPP systems

Transaction attribute	**Description**
Asset specificity	Mixed: Investments on FCEVs will not be made solely for V2G, as their main purpose is mobility.
Frequency	Recurrent: The use of FCEVs for V2G can be more or less regular and/or frequent. However, the CaPP concept assumes they are used recurrently rather than occasionally.
Uncertainty	There is some level of uncertainty regarding when a FCEV will be used for V2G, since it does not depend only on the driver's preferences for V2G supply.

When taking a CaPP system as a whole, for example the CaPP microgrid, there are more interactions and transactions that need to be governed by institutions: from the role of providing power to the households, to the generation and storage of hydrogen and the sales in the refilling station. However, we focus on vehicle-to-grid as the main coordination challenge in CaPP systems and therefore we explore the contractual relationships that govern transactions between fuel cell vehicle drivers and the aggregator. Moreover, different ownership structures are possible in CaPP systems, depending on how they are developed. For example, a CaPP microgrid could either have community, utility, private, or hybrid ownership structure (Gui et al., 2016). However, the form of *governance of vehicle-to-grid* transactions would not change within the different system ownership structures.

2.4. Agent-based modeling of socio-technical systems

Modeling and simulation is a commonly used approach when analyzing questions on design, development or change in socio-technical systems. Models allow us to better understand systems, to improve the performance of systems, to predict the future, or to design new systems (Chappin, 2011). When dealing with future developments in the energy transition, modeling and simulation techniques can help in understanding how a system innovation may be implemented. New rules and institutions can be tested and explored under different future scenarios.

In this research we use agent-based modeling and simulation (ABMS), a modeling approach widely used for simulating natural and social systems (Epstein, 1999). Agent-based models have been proven to be useful in structuring and capturing and structuring complex socio-technical systems (Ghorbani, 2013; K. Van Dam, 2009). To facilitate the formalization of socio-technical systems in agent-based models, K. Van Dam (2009) presents an ontology of socio-technical systems, where the system components are represented as physical nodes (physical components) and social nodes (actors) and edges (links). In this type of ontology, contracts are represented as physical edges between social nodes, but institutions are not conceptualized separately.

Using the the Institutional Analysis and Design (IAD) framework (Ostrom, 2011), Ghorbani (2013) presents a framework to structure socio-technical systems, where institutions are modeled explicitly, in the form of rules. In this case, the grammar of institutions of Crawford and Ostrom (1995) is used to formulate institutions (rules) into actions that are *"required, prohibited, or permitted"*.

K. H. Van Dam et al. (2013) propose a practical guide for building agent-based models, starting from the problem formulation through the model use in 10 steps. This method shows that four steps are required before the software implementation, where the modeler needs to formulate the problem and conceptualize it before formalizing it. After the software implementation, a rigorous model verification step is required to make sure that the model *"is doing what it was built to do"*. After the experimentation and data analysis, a model validation is carried out to assess whether the *"right model was built"*. Finally, the model can be used to answer the question that it was built to address.

In an approach that helps both formulating and describing agent-based models, Grimm et al. (2006) propose *"a standard protocol for describing individual-based and agent-based models"*, namely the ODD protocol. The name stands for *Overview*, *Design concepts* and *Details* as the categories described that encompass the concepts upon which an agent-based models are built. The *Overview* includes a description of the *Purpose*, followed by the *State variables and scales*, and the *Process overview and scheduling* in the model. Then, the *Design concepts* provide a description of how several aspects related to complexity are addressed in the model. Finally, in the *Details*, the model *Initialization* and *Inputs* are described, as well as the *Submodels*. A notable element in the ODD protocol that helps in describing models of complex systems is the *Design concepts* category, which is based on answering the following questions:

- **Basic principles**: What are the general concepts, theories, hypotheses, or modeling approaches used in the model?

- **Emergence**: What are the model's results and outputs. Do they 'emerge' from the actions and adaptive behavior of agents, or are merely imposed by rules.

- **Adaptation**: What are the adaptive behaviors of the agents? How are they modeled, via direct or indirect objective-seeking?

- **Objectives**: How is the performance of an agent measured in the model? What measures are used to model the objectives of agents?
- **Learning**: Do the adaptive characteristics change in time?
- **Prediction**: Is prediction modeled explicitly through memory, learning, or is it implied through adaptive behavior?
- **Sensing**: What variables from the environment do the agents take into their decision-making? What are the uncertainties? how is the sensing behavior modeled?
- **Interaction**: Do agents interact directly or indirectly?
- **Stochasticity**: Are there any stochastic processes in the model, and how are they used?
- **Collectives**: Are agents aggregated in the model? Are collectives imposed or do they emerge?
- **Observation**: What are the main outputs that allow to observe the internal and aggregate-level behaviors?

2.5. Research approach

The research approach of this thesis consists of two main parts: 1) the conceptualization of the system using the socio-technical system operation framework and 2) the formalization and implementation of the system in an agent-based model followed by simulation experiments. In this section we explain the socio-technical system operation framework and discuss how CaPP systems can be conceptualized accordingly. Then, we describe shortly the formalization in agent-based models. Finally, we define how the framework is used throughout the thesis.

2.5.1. Conceptual framework

Building upon the theories and concepts described above, we define the framework of this research, which we use to analyze the operation of the Car as Power Plant. As shown in Fig. 2.3, we present the three pillars in the socio-technical system operation: the Physical System (PS), the Actor Network (AN), the Institutions (I) in place, and the interactions between them. The system's performance at the operational level is directly influenced by the operation of the individual components and the interactions. In the long term, the evolution of the system can be seen as a result of the continued operation. In this section we describe how our systems are analyzed and described based on the conceptual framework before they are formalized in agent-based models.

Timescale Time is an important aspect in socio-technical systems that are constantly changing and evolving. Different timescales can be used to analyze socio-technical systems depending on the actions and decisions that are the object of analysis. As Table 2.2 shows, they can be analyzed from a long term or evolutionary perspective by

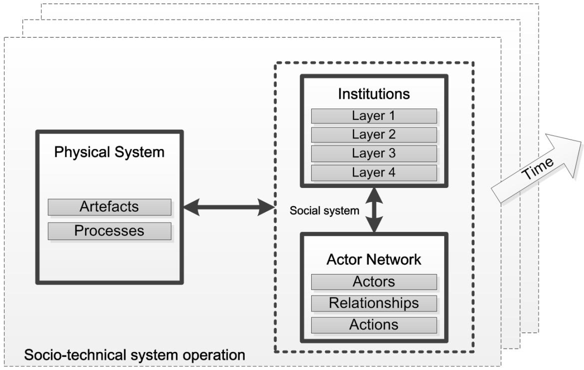

Figure 2.3: Conceptual framework of this research

Table 2.2: Timescales in socio-technical systems analysis

Timescale	**Unit of time**	**Time horizon**
Long term	Multiple Years	Decades
Strategic	Yearly	5 - 10 years
Operational	**Hourly**	**Week/Month/Year**

looking into changes that occur within multiple years or decades, throughout decades or centuries, respectively. In the medium term, policies or strategic investment decisions may be tested, and the effect of actions that occur on a yearly basis is studied throughout several years. Finally, in the short term, actions occurring in a time span of an hour (or less) may be analyzed throughout a day, week, month or a year. In this research we aim to analyze new actions, interactions and feedbacks in future systems at the operational level to help understand their development on the long term. Therefore, we choose the short-term timescale to conceptualize the actions in the system in one-hour time steps.

Physical system The physical system consists of the technical and physical components: the devices and infrastructure necessary to produce, store, or transport energy. For the Car as Power Plant concept, this means that the production of hydrogen, its use in vehicles - both for transportation and vehicle-to-grid - have to be explicitly defined. This includes not only the components, but also their operation, i.e. the formulation of the physical flows and processes over time. For each CaPP system analyzed, the components may differ, as well as the rules to operate the system.

Actor network Next to the physical system, the actors involved in the operation of the system have to be conceptualized. In this case, we focus on the fuel cell vehicle drivers and the entity managing the V2G operation, e.g. the aggregator. In the actor network there are multiple actors with heterogeneous properties that make decisions and perform actions following behavioral rules. While we do not base the conceptualization of actors on behavioral psychology, we assume that actors are not 'rational, optimizing' entities but are 'boundedly rational' (Simon, 1972) and thus we apply heuristic rules to represent the actors' actions and decision-making. For each CaPP system studied, the network of actors may differ as well.

Institutions The operation of fuel cell cars as power plants in a CaPP system will be influenced by the institutional environment (policies, regulation), the institutions of governance (markets, contracts) and the resource allocation (prices, costs). However, as mentioned earlier, the main CaPP aspects to analyze are the vehicle-to-grid transactions and related actions. Therefore the main focus is the set of rules needed to manage the V2G transactions. For this research, the aim is to explore Layer 3 in detail, while including assumptions and some explicit formulations and even operationalization of other institutional layers, where possible.

By applying the conceptual framework in this thesis we aim to analyze CaPP systems as shown in Figure 2.4. As indicated in the grey-scale key in Table 2.3, the goal is to analyze the physical system operation, actors' actions, and the role of institutions (mainly L3) by taking into account the time-dependent changes. For this thesis the operational timescale is chosen and therefore we focus on processes and actions occurring in the span of an hour. The dynamic aspects of the socio-technical systems can be explored through agent-based modeling and simulation.

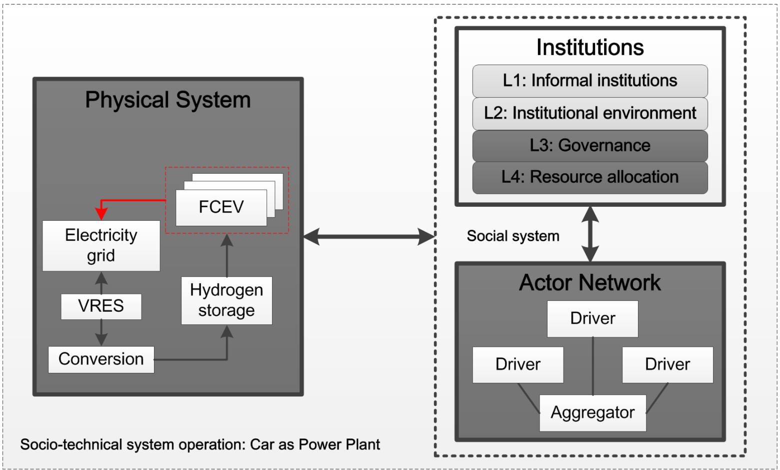

Figure 2.4: Level of analysis of CaPP sytems expected in this thesis

Applying the research approach involves explicitly defining in each model the interactions and links between the the physical and social systems, and between the actor network and institutions. The physical system and actor network are linked in terms of ownership (e.g. actor (*driver*) – physical component (*FCEV*)), but also the decisions that actors make on the physical components at the operational level. For instance, the use of fuel cell cars is partly influenced by drivers' driving patterns. On the other hand, the use of fuel cell vehicles for V2G changes the fuel level in the vehicles,

Table 2.3: Key to indicate level of analysis of socio-technical system components

Level of analysis	Description
Implicit	Components are not included in analysis but assumed
Static	Components are explicitly defined and analyzed
Dynamic	Time-dependent changes are analyzed

prompting drivers to refill their tank.

The institutions and actor network are linked by the rules that are used by the actors. This may concern the way actors act or interact with each other. On the other hand, actors choose the rules they follow (e.g. defining contract conditions), influencing the system behavior. Finally, the physical system can influence institutions indirectly by affecting the prices and quantities of goods and services defined by the actors. Moreover, institutions are linked to the physical system through the rules that affect the operation of physical processes, which is executed by actors as they follow certain rules.

2.5.2. Agent-based modeling and simulation

The conceptualization of CaPP systems is followed by their formalization in agent-based models, following the steps in (K. H. Van Dam et al., 2013). In this thesis we describe and document the models using the ODD protocol (Grimm et al., 2006) discussed above. To answer questions about the Car as Power Plant concept, we focus on two cases or types of applications with different characteristics: the *CaPP microgrid* and the *Car-Park Power Plant*. Each system is formalized in agent-based models. The model and experiments are described as follows:

1. System description
2. Agent-based model description
    (a) Overview
    (b) Design concepts
    (c) Submodels
    (d) Input parameters and data
    (e) Model assumptions
    (f) Model verification
    (g) Model validation
3. Experiments: Initialization, results and sensitivity analysis

2.5.3. Approach throughout this thesis

The proposed research approach is used in this thesis to answer the main research question through the four sub-questions. Fig. 2.5 shows the research approach, which consists of two parts.

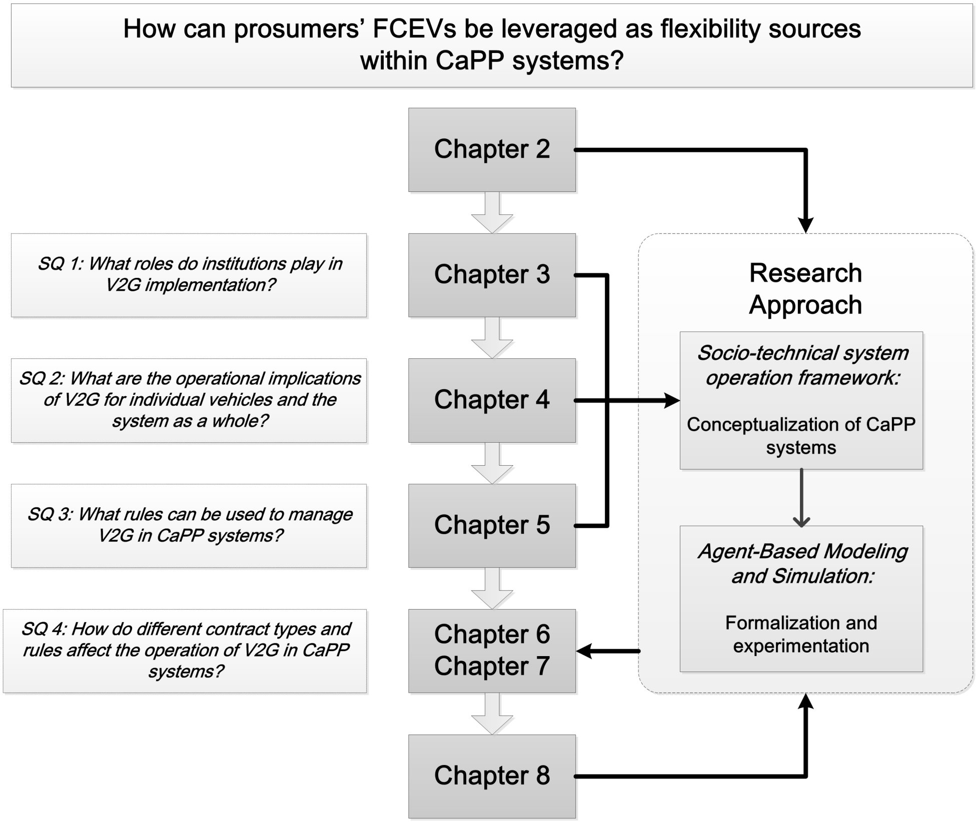

Figure 2.5: Structure of this thesis in relation to the research approach and the research subquestions

Chapters 3 to 5 are used as inputs to aid the conceptualization of CaPP systems, while answering three of the four research sub-questions. Chapter 3 is focused on the role of institutions in relation to vehicle-to-grid, which is needed in order to define the institutions at different levels in CaPP systems. Then, Chapter 4, which focuses on the physical operation of a CaPP system and its effect on the individual drivers, helps understand the implication of V2G operation on individual drivers and the system. Chapter 5 delves into the conceptualization of contracts for vehicle-to-grid, which are crucial for the conceptualization of CaPP systems as socio-technical systems.

Finally, all the outcomes are used to conceptualize and formalize two CaPP systems in agent-based models. The simulation experiments and outcomes provide insights about how different rules affect the operation of CaPP systems, and also lead to conclusions and reflections about the approach used in this research.

3

Literature review

3.1. Introduction and scope of this review

In this chapter we answer the first research sub-question: *"What roles do institutions play in vehicle-to-grid implementation?"*. For this, we analyze the literature on vehicle-to-grid feasibility and implementation that provides insights on one or more institutional layers.As mentioned in Chapter 2, we do not take into account the informal institutions in Layer 1 of Williamson (1998)'s framework.

We classify the literature topics into three categories, based on the main type of institutions addressed: 1) Techno-economic assessments of V2G, 2) V2G contracts, 3) Institutional environment for V2G. In each literature category, we use the conceptual framework of this thesis to indicate the timescale used and to compare to what extent the socio-technical system components are considered. Using the grey-scale key in Table 2.3 presented in Chapter 2, we indicate the corresponding level of analysis in the physical system (PS), actor network (AN) and institutions (I).

Furthermore, we discuss the role of each type of institution in the implementation of vehicle-to-grid. Given the limited number of studies that focus on FCEVs alone, we include publications where all electric drive vehicle (EDV) types are considered. We do not include publications that focus on: impacts of electric vehicles or V2G on the electricity system, optimal scheduling of electric vehicles/unit commitment models for V2G, smart charging of plug-in electric vehicle, or adoption of EDVs.

3.2. Techno-economic assessments of V2G

Vehicle-to-grid was first introduced in 1997 by Kempton and Letendre (1997), with all EDV types as possible power sources. The first few publications thereafter (Kempton & Kubo, 2000; Kempton & Tomić, 2005a; Letendre & Kempton, 2002) focused on the potential of EDVs in supporting the power systems by providing different types of services and/or power. Although FCEVs were also considered at the beginning, there are only a limited number of publications that continued considering FCEVs, either exclusively or together with other EDVs.

The techno-economic assessment of V2G integration refers to the analysis of the technical and economic viability of EDVs as power sources. This typically involves an economic assessment that takes into account technical characteristics of electric vehicles such as the capacity, the energy available, etc. Such assessments are usually focused on the national electricity markets, but the use of vehicles to provide electricity to buildings is explored as well, especially using FCEVs. Table 3.1 shows the timescale of the analyses and to what extent studies in this category cover the physical and social aspects of the system.

Table 3.1: Literature overview: Techno-economic assessments of V2G

Reference	**EDV type**	**Timescale**	**PS**	**AN**		**I**	
					L2	**L3**	**L4**
Kempton and Tomić (2005a),Williams and Kurani (2007), Kempton and Kubo (2000)	All	–					
Kempton and Tomić (2005b); Tomić and Kempton (2007)	All	–					
Romeri (2011), Mullan, Harries, Br??unl, and Whitely (2012)	FCEV/EV	–					
Turton and Moura (2008)	All	Long term					
Gough, Dickerson, Rowley, and Walsh (2017)	EV	Operational					
Kissock (1998), Lipman (2001), Lipman, Edwards, and Kammen (2004)	FCEV	Operational					

Vehicle-to-grid potential in electricity markets

When assessing the potential of V2G in electricity markets, the first approach used was to estimate the annual capacity of EDVs in the system, the hours of operation throughout a year for each of the available markets or type of power. This type of analysis can provide an overview of the expected revenues and costs using average electricity prices (Kempton & Kubo, 2000; Kempton & Tomić, 2005a; Tomić & Kempton, 2007; Williams & Kurani, 2007). In terms of the physical system, Kempton and Tomić (2005a) consider the capacities of different EDVs and the available power for different types of vehicle-to-grid power: peak power, spinning reserves and regulation. The conditions for V2G operation in different markets is defined to estimate the annual revenues and costs for V2G in the United States. This is done for a range of fuel cost and electricity price assumptions. The economic performance is calculated from the perspective of an average driver. Actors and their characteristics or behaviors are not explicitly taken into account, but are assumed to be there. Drivers are mentioned when discussing the vehicles' stored energy and preferences regarding V2G, which are incorporated from interview results. To calculate the potential of EDVs for regulation, spinning reserves and peak power, drivers are assumed to be plugged in and available 18 hours a day.

Table 3.2 shows the characteristics of the different power markets and services considered in the study. An important conclusion is that EVs *"cannot provide baseload power at a competitive price"*. However, they can provide other type of power and

Table 3.2: Vehicle-to-grid in wholesale markets and ancillary services, derived from Kempton and Tomić (2005a)

	Wholesale markets		**Ancillary services**	
	Baseload	**Peak Power**	**Spinning Reserves**	**Regulation (up)**
When	Round the clock, all year round.	Few hundred hours per year. Duration around 3-5h.	Short periods of generating power. Called 20 times per year, 10 min to 2h per call.	Called around 400 times/day, for a few minutes (1-4 min)
Characteristics	Low capital costs, low response time, low electricity price	High capital costs, high response time, high electricity price	24h availability, energy and capacity payment.	Response needed within 1 minute of grid operator signal. Contract for amount of power available.
V2G?	Not competitive	Economic under certain circumstances	Yes, for FCEVs rather than EVs, due to higher storage capacity	Yes, especially for EVs

services to support the grid, and they can be used to alleviate overload problems in distribution lines (Ipakchi & Albuyeh, 2009).

Kempton and Tomić (2005a) show that EVs that have the electrical energy stored in a battery are most suitable for providing upward regulation capacity. To provide this service, the EV is connected to the grid and the TSO can control the output from the battery to balance the supply and demand by discharging electricity from the vehicle's battery. The results indicate that when providing ancillary services (spinning reserves, regulation), drivers may end up with losses when considering only energy payments. However, capacity payments can make up for the losses. Results show that while EVs are more suitable for providing regulation services, fuel cell vehicles are more suitable for providing spinning reserves and peak power. Kempton and Kubo (2000) provide a similar analysis for the Japanese Kanto region. In this case, the authors do not specify the availability in order to assess the value of V2G for the electricity system.

Kempton and Tomić (2005b) further analyze the feasibility of using V2G for supporting large-scale renewable generation. Technical aspects of variable renewable energy sources (photovoltaic and wind) are analyzed against vehicle characteristics to determine the size of fleet needed. Some characteristics of drivers are mentioned, but not discussed in detail.

Tomić and Kempton (2007) analyze the capacity and economic potential of V2G using two fleets with different EDV types. Similarly as in (Kempton & Tomić, 2005a), an annual analysis is carried out, considering the conditions for V2G operation in different markets. Similar assumptions are made regarding actors, although it is explicitly mentioned that the use of a vehicle for V2G would be defined *"within the limits set by the driver or the fleet operator"*. With this, they refer to the amount of energy needed for daily trips. The authors use a uniform random distribution to model plug-in behavior and availability. This results in a range of availability of 14 to 20 hours per day, which is used to estimate the value of using vehicle fleets to support the grid.

Williams and Kurani (2007) provide a review of the main V2G concepts to provide a framework for using FCEVs as distributed energy sources. The technical characteristics of FCEVs and other electric vehicles are considered, as well as the revenues and costs. Like in previous studies, the role of drivers is not explored in detail. It is assumed by the authors that vehicles would be available around 12 hours/day, 11 months/year.

Another type of analysis focuses more on the cost/remuneration of vehicle-to-grid to analyze its future potential. Romeri (2011) provides a cost analysis of V2G with FCEVs based on the data of 2009 and the cost and technology targets for 2015. In this case, only the technical characteristics of FCEVs and the costs are calculated and a comparison is given with respect to other electricity sources. Again, the availability of vehicles for V2G is not considered or mentioned. In this case, the conditions for activation of V2G are also not considered. Mullan et al. (2012), on the other hand, calculate the yearly budget for capacity payments to participating vehicles for the case of Western Australia. These capacity payments are considered necessary to encourage the availability of vehicles, but the analysis shows that it may not be sufficient to incentivize drivers. To determine the availability of vehicles, the authors assume that at most, 20% of the participating vehicles would be driving at any time. Therefore, 80% would be available for V2G. The condition for activation of V2G is not specified, as the focus is on the capacity payments for spinning reserves - based on availability.

Kempton and Tomić (2005a) discuss that to have a more in-depth analysis of the annual revenues in different markets, it is necessary to look at the hourly market prices and assume V2G activation whenever cars are available and prices are above V2G costs. Gough et al. (2017) present a model with a half-hourly simulation, in which participation of electric vehicles in the wholesale electricity market and in a science park are analyzed. While there is no focus on the aggregator or the drivers, vehicles are modeled as agents, and their income is calculated. A probabilistic model is used to represent the heterogeneous driving behavior of vehicles, and this is used to assume their availability for V2G. Results show that participation in the wholesale market with seems to be most profitable when combined with the capacity market.

In a long-term analysis, Turton and Moura (2008) determine the capacities of electric vehicles for power generation in different world regions. The activation of V2G in the different markets is assumed by the number of hours that a vehicle would typically participate in supplying peak power or ancillary service during a year. The role of aggregators is discussed, as well as the need to maximize vehicle availability through the engagement of customers. However, the role of actors is not discussed further. Vehicles are assumed to be available 50% of time.

Local integration of FCEVs

The literature on implementation of vehicle-to-grid with FCEVs in electricity systems is rather limited. The most in-depth analyses deal with the integration of FCEVs in local energy supply – more specifically at the building level.

Kissock (1998) investigates the feasibility of using both the electricity and heat generated in FCEVs to supply commercial and residential buildings. The lifetime of the fuel cells is not considered to be a limitation. The author uses a simulation model to compare the performance of FCEV cogeneration in residential and commercial settings in states with different climates. For this, the hourly operation of each setting is modeled, and different V2G operation strategies are compared. While actors and their behavior are not considered, scenarios for vehicle availability are used in the analysis. The results show that significant annual savings can be generated in residential and commercial settings by using FCEV for cogeneration.Electricity purchased from the utilities can be greatly reduced, by 47 to 65% in residences and by 86 to 93% at workplaces, and heat from FCEVs can replace more than 96% of thermal energy requirements. The study concludes that FCEV cogeneration is feasible and that it *"merits consideration as an innovative element in the portfolio of options for the distributed utility of the future"* (Kissock, 1998). Vehicles are assumed to be parked and available from 18h to 7h at home and from 8h to 17h at commercial buildings, during weekdays. In the simulation runs, different daytime vs. night-time availability ratios are assumed (e.g. 1000:100, 500:50). The activation of V2G is assumed to be based on the local load. Operational strategies are explored, regarding the use of heat, and whether FCEVs are used for electric load-following or thermal load-following.

Further studies only consider the generation of electricity from FCEVs. In a study on the economics of fuel cell power, Lipman et al. (2004) compare stationary and motor vehicle Proton Exchange Membrane (PEM) fuel cell systems by estimating their potential costs for distributed power, for the period 2010-2015. This publication is a follow-up of previous work presented in a conference publication (Lipman, 2001), where a similar analysis is presented. As opposed to Kissock (1998), Lipman et al. (2004) emphasize that cogeneration is not suitable for vehicle fuel cell systems due to overheating and the need of a heat exchange connection results in more cost and complexity. In this case, FCEV were considered to be connected to a house/building to serve the load and to feed the excess electricity to the grid. Therefore FCEV power is used to replace the power that would be otherwise used from the grid, especially during peak hours. The net revenues from FCEV-based power are represented by the net savings incurred through the use of FCEV power instead of grid power. Taking into account the capacity and revenues, the authors claim that by using stationary and vehicle fuel cells as distributed generation systems, it would be possible to *"reduce the need to operate peak power plants and to construct new ones to meet peak demand growth"* (Lipman et al., 2004). The feasibility of FCEVs is further emphasized by arguing that they could be operated continuously by being connected to a hydrogen inlet. This would remove the energy capacity constraint in the fuel cell vehicles.

The results show that the most profitable type of setting to provide power with FCEVs is in office buildings, under a net metering program and a TOU tariff. However, for FCEV power to be competitive, natural gas prices need to be low. Moreover, it is considered that the durability of a fuel cell system must be in the order of 10,000 hours to be able to use it both for transport and power generation (Lipman et al., 2004). In a residential setting, it is most suitable to use the FCEV only during peak periods, or for emergency backup power. While there is a strong focus on the operation of the system and economic performance, the role of actors is not analyzed in the models. Lipman (2001) assume that vehicles are available from 8 to 10 hours/day, while Lipman et al. (2004) assume that vehicles are available 95% or the time. Two operational strategies that define the activation of FCEVs for V2G are compared: net metering during peak hours, and load-following.

The age of the publications that explore the use of FCEVs for V2G shows how the initial interest in all EDV types started to shift towards BEVs and PHEVs, possibly due to their faster commercialization and adoption. However, the recent introduction of new FCEV models in the market and the discussions on the role of hydrogen in future energy systems demonstrate that more research is needed on the potential of FCEVs for V2G services.

3.3. Vehicle-to-grid contracts

From the governance perspective, the main topic in V2G literature is the use of contracts to ensure a certain level of participation and availability for V2G. A vehicle-to-grid contract is, in essence, a set of rules that defines the conditions for using EDVs as power sources. Table 3.3 shows the timescale of the analyses and to what extent studies in this category cover the physical and social aspects of the system.

Guille and Gross (2009) propose a framework to integrate Battery Electric Vehicles (BEVs) in the grid by providing demand response and vehicle-to-grid. The central actor and key enabler is considered to be the aggregator, which can be the TSO or an energy service company that has contracts with households of BEV owners. The

Table 3.3: Literature overview: Vehicle-to-grid contracts

Reference	EDV type	Timescale	PS	AN	I		
					L2	L3	L4
Guille and Gross (2009), Parsons, Hidrue, Kempton, and Gardner (2014)	All	–					
Broneske and Wozabal (2017)	All	Operational					

main advantage is that the aggregator has a large purchasing power that a single BEV owner could not have. A package deal is proposed, consisting of preferential rates for purchasing the battery, but also discounts for charging and parking. The obligations indicated in the contract consist of plugging in at times that are predefined in the contract. Failing to comply with the contract terms leads to penalties.

Based on the concept of contracts for vehicle-to-grid Parsons et al. (2014) investigate in a choice experiment the effects of V2G revenues on consumer preferences towards the purchase of BEVs in the United States. The possibility of earning revenues through V2G is included in the BEV attributes, as well as the required plug-in hours to provide such services. Parsons et al. (2014) describe two options for the relationship between the aggregator and EV driver: a contractual and a non-contractual form. The former would involve obligations for the service and a yearly cash payment, and the second, a free participation and 'pay-as-you-go' type of remuneration. The contract consists of required plug-in hours (ranging from 5 to 20 hours) and a guaranteed minimum range (ranging from 25 to 175 miles). One of the conclusions is that the upfront payments for V2G to drivers might not be enough to participate in V2G. The authors found that users value flexibility in plug-in time and that signing contracts are seen as an inconvenience. Additionally, drivers have uncertainties about the earnings they could make through V2G. Consequently, the concept seems to be attractive only if high prices are paid to drivers for the V2G contracts. A strategy proposed in the paper is to allow drivers to provide V2G services in a flexible way, or to pay them in advance for signing a V2G contract.

One econometric study quantifies the influence of contract parameters on the economic potential of V2G in the German secondary reserve markets (Broneske & Wozabal, 2017). The contract parameters used are those presented in (Parsons et al., 2014). Driver characteristics from mobility data are used to assume contract parameters (based on the theoretical participation potential) and to make subsets of drivers with similar characteristics. Using the subsets, the value of different vehicle characteristics for the aggregator are determined. Although the authors use market data of a whole year, they extract two weeks with the highest and lowest reserve market demands to calculate the optimal car pool size, as well as the annual profits. Broneske and Wozabal (2017) conclude that the value of certain contract parameters for the aggregator depends on the characteristics of the market, i.e. markets where more energy is supplied will value drivers that are able to provide enough energy (lower guaranteed minimum range) while also providing enough availability, while markets where less energy is supplied, the availability (plug-in hours) will be more valued. Moreover, higher guaranteed driving range requirements decrease profits, as they limit the energy available for V2G. Thus, the profit potential can be calculated with the vehicles' capacities and market prices, but ultimately it depends on on the conditions defined in the agreements between the driver and the aggregator.

In this sub-topic, the availability of vehicles is defined in the vehicle-to-grid contract. Parameters such as the plug-in duration and timing are defined, while the amount of energy available can be limited by the guaranteed energy level. Therefore, contracts include not only rules on availability, but also on the conditions for operating the vehicles. Behaviors of actors, however, are not explored in relation to the contracts or the physical system operation.

3.4. Institutional environment for V2G

In this final sub-topic we present the literature that is concerned with the conditions in the institutional environment (regulation, policies) to enable the integration of vehicles through V2G. Table 3.4 shows the timescale of the analyses and to what extent studies in this category cover the physical and social aspects of the system.

Table 3.4: Literature overview: Institutional environment for V2G

Reference	**EDV type**	**Timescale**	**PS**	**AN**		**I**	
					L2	**L3**	**L4**
Kempton and Tomić (2005b); Tomić and Kempton (2007)	All	–					
Sovacool and Hirsh (2009), Uddin, Dubarry, and Glick (2018)	All	–					
Freeman, Drennen, and White (2017), Richardson (2013b)	EV	Operational					

One of the aspects from the institutional environment that is widely assumed in the literature is the need for aggregation in order to exploit V2G power from vehicles (Kempton & Tomić, 2005a). In the current electricity system, generators make contracts with operators to provide spinning reserves or regulation in blocks of 1 MW. Therefore, it is usually assumed that an *aggregator* will participate in the electricity market on behalf of electric vehicle owners.

Institutional conditions and barriers

Tomić and Kempton (2007) indicate that although V2G is feasible, some of the institutional barriers should be addressed are: 1) lack of vehicle aggregators, 2) broadcasting of regulation signal, 3) regulation service rates not available at the retail level, 4) no mass production of V2G-ready vehicles, 5) need for new standards, to cover the quality of V2G power. Kempton and Tomić (2005b) also mention some strategies in the transition path from a market perspective. Moreover, they indicate the type of institutional environment in which the development of V2G would be specially more favorable. This includes countries or regions that have: 1) needs for increased flexibility, but want to avoid grid expansion, 2) under-developed grids, 3) have relatively high costs for ancillary services, 4) have policies for technology development, 5) have renewable energy goals (especially wind). Specific policies to encourage vehicle-to-grid are not discussed.

Sovacool and Hirsh (2009) analyze the benefits and barriers for V2G implementation. The authors claim that even if it were technically feasible, it could not be widely accepted. More importantly, they emphasize that there is a *"host of socio-technical considerations"* to take into account for a successful V2G transition. By reflecting on the history of the Zero Emission Vehicle (ZEV) policy in California and the California Air Resources Board (CARB) mandate in the 1990s, the authors make an analysis of the barriers that could also hamper the V2G transition. They indicate that there are important institutional obstacles to change the current infrastructure, systems, and the involved actors, who are reluctant to such system-wide changes. They do not discuss, however, how to overcome such barriers. Uddin et al. (2018) consider the battery technology aspects as well as the policy implications and regulatory issues with V2G. The authors conclude that for V2G to be feasible, it is key to develop the required infrastructure as well as the appropriate remuneration structure to compensate battery degradation. Changes in electricity markets to enable aggregate participation of EVs is also mentioned. As Table 3.4 indicates, these issues are analyzed without considering the operation of the system.

Policies to encourage V2G

To increase profitability of V2G and attract drivers, Richardson (2013b) introduces a premium tariff rate for V2G power. Three markets are considered: peak power, operating reserves, and regulation. Based on the hours of participation per year, a premium tariff is calculated to provide a 11% rate of return.The author uses historical electric prices to assess the profitability of V2G. Possible changes in future electricity prices caused by increasing V-RES penetration are not considered. Freeman et al. (2017) calculate the profits for a driver during a five-year period using locational marginal price data. The authors use different V2G participation scenarios to calculate the profits that a driver can realize: work-hour price-taker V2G, arbitrage-guide V2G with perfect information, and user-defined selling price V2G. With different strategies, the maximum average savings for a driver throughout 5 years is of $201. With a carbon tax of $50, this amount increases by $31.

The availability of vehicles in (Richardson, 2013a) and (Freeman et al., 2017) is estimated by using driving data and assuming that vehicles are available whenever they are not parked. The activation criteria are only mentioned in (Freeman et al., 2017), where three V2G scenarios are used, which represent possible driver strategies to participate in V2G. In this case, the role of the aggregator as an intermediary is not mentioned. In (Richardson, 2013b), operational V2G strategies are not used, but the premium tariffs are calculated for different percentage of peak power provision during a year.

3.5. Discussion and conclusions

3.5.1. Overview

In this chapter, we reviewed literature on V2G integration that focus on institutions in Williamson's Layers 2, 3, and 4. All institution types were reported to influence the integration of EVs in electricity systems.

Techno-economic assessments

Techno-economic assessments include feasibility studies that focus on vehicle characteristics such as capacity, suitability of different markets, and economic potential. Initial studies consist of static analyses calculating expected revenues in different markets based on average figures. Operational studies include hourly prices and aggregated revenues over a year. Other studies focusing on the use of FCEVs for local energy generation, determine the revenues of V2G from different operational strategies. This type of analysis can be helpful in understanding under what conditions vehicles can profit from V2G participation.

V2G contracts

Literature on this topic shows that V2G contacts can be used to define the rules needed to manage the availability and conditions for using FCEVs as power plants. Contracts are mentioned as a strategy to engage drivers in V2G (Guille & Gross, 2009), or to evaluate the influence of V2G in EV adoption (Parsons et al., 2014). In these studies, the perspective of drivers is also considered. However, the implications of such contractual conditions on vehicle-to-grid operations is not investigated. A more recent publication uses these concepts to explore how contracts for battery EVs affect driver profits (Broneske & Wozabal, 2017). In this case, actors are not explicitly modeled, but the driving characteristics of a pool of drivers are used as an extension of the actor characteristics and the contractual parameters chosen by each one. This shows clearly that contracts can be designed as a set of rules to manage V2G transactions.

Institutional environment

The institutional environment in relation to V2G is explored either qualitatively or quantitatively. For the feasibility of V2G in the long-term, the barriers for introducing V2G can be explored without considering the time-dependent changes in the physical system and the actor network. This perspective, however, shows the constraints in the social system – not only the norms (Layer 1) but also the political environment (Layer 2). As such, it is focused on policy advice. On the other hand, more quantitative approaches are used to perform analyses similar to operational techno-economic assessments, but including the use of policies that can encourage the implementation of V2G.

3.5.2. Positioning of this thesis

The three institutional perspectives show the roles that institutions play in vehicle-to-grid implementation from different timescales and perspectives. The literature shows that the management of V2G transactions requires a deeper analysis of the role of contracts in the operation of systems with vehicle-to-grid. Moreover, the literature on V2G contracts shows that the interactions between contracts, physical system operation, and actor behavior is yet to be explored. In general, the socio-technical systems perspective is rare: only Sovacool and Hirsh (2009) address "socio-technical" obstacles, albeit in a qualitative manner.

Table 3.5: Timescale and level of analysis of each socio-technical system pillar throughout this thesis

Chapter	**Timescale**	**PS**	**AN**		**I**	
				L2	**L3**	**L4**
4: Implications of V2G operation for drivers	Operational					
5: Vehicle-to-grid contracts for prosumers	–					
6: V2G contracts in a microgrid	Operational					
7: V2G contracts in the electricity market	Operational					

Therefore, the goal of this thesis is to explore the operation of V2G from a socio-technical system perspective, and analyze how rules can be used to leverage prosumers' FCEVs as power sources in future low-carbon systems. To do this, we focus on the processes of the physical system, the actions of actors and the institutions (especially in Williamson's Layer 3) needed to guide their interactions, at the operational level. Using the grey-scale key used in this chapter, we indicate in Table 3.5 the level of analysis of the three system components throughout this thesis.

4

Operation of a Car as Power Plant microgrid

4.1. Introduction

In this chapter we address the research sub-question: *"What are the operational implications of vehicle-to-grid participation for individual vehicles and for the system as a whole?"*. As indicated in Chapter 2, answering this research question will contribute to the conceptualization of CaPP systems as socio-technical systems, as it helps uncover key aspects related to the participation of FCEV drivers. From the technical components of the operation of this system, we want to derive lessons on the implications on the behavior of actors and the rules that will have to be defined and explored with respect to vehicle-to-grid at the operational level.

To understand the relationship between the system performance at the operational level and the implications for individual vehicles, we build a MATLAB simulation model of a *Car as Power Plant microgrid* system. We explore the operation of the microgrid focusing on the main physical processes. We do not model explicitly the actions of actors in this chapter, but make assumptions about their behaviors and the availability for V2G.

The CaPP microgrid depicted in Fig. 4.1 is located in a residential neighborhood of 200 households, each one equipped with a rooftop solar photovoltaic (PV) system. The energy management system (EMS) balances the supply and demand of electricity, using dispatchable generation and storage. When there is a shortage of PV generation, FCEVs are used to supply power. The surplus PV generation is used to operate the electrolyzer, in which electricity and water are converted to hydrogen. This is then compressed (C) and stored (S) in the central refilling station. There is an external wind-to-hydrogen system that consists of a wind turbine and an electrolyzer. The hydrogen produced is compressed and transported directly to the refilling station in the neighborhood via a pipeline. The role of the microgrid with respect to the main grid is that of a net exporter,

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Parts of this chapter have been published in (Park Lee & Lukszo, 2016). The work was devised, conceptualized and executed by Park Lee.

since it will use FCEVs before importing power, and will export whenever the capacities of the electrolyzer and/or hydrogen storage are exceeded.

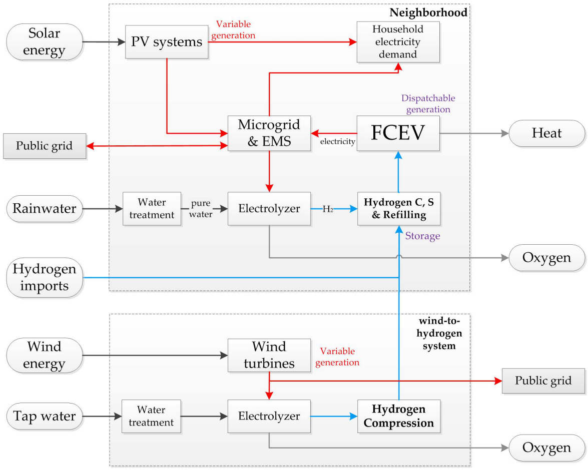


Figure 4.1: Description of the CaPP microgrid system

4.2. Model description

In this section we present the problem formulation of the CaPP microgrid model implemented in Matlab. The assumptions are presented in Table 4.1. The flows and relationships between the system components are shown in Fig.4.2. The red arrows indicate flow of electricity, and the blue arrows indicate flow of hydrogen. The imports of hydrogen and exchanges with the main grid are indicated in dashed lines. The symbols used in this section are explained in the Nomenclature in Appendix B.4. The equations for every component of the CaPP microgrid model are shown below.

4.2.1. System balance

The imbalance between the PV generation and load is expressed by K_t:

$$P_t^{PV} - P_t^{load} + K_t = 0 \tag{4.1}$$

$$K_t = \sum_{i=1}^{N} P_{it}^{fcev} - P_t^{el1} + P_t^{ex1} \tag{4.2}$$

$$if \begin{cases} K_t > 0 & \sum_{i=1}^{N} P_{it}^{fcev} > 0,\ P_t^{el1} = 0 & (4.3a) \\ K_t < 0 & \sum_{i=1}^{N} P_{it}^{fcev} = 0,\ P_t^{el1} > 0 & (4.3b) \\ K_t = 0 & \sum_{i=1}^{N} P_{it}^{fcev} = 0,\ P_t^{el1} = 0 & (4.3c) \end{cases}$$

The electrolyzer is operated when there is a surplus of PV generation (P_t^{el1}). FCEVs are used to provide power when there is a shortage. Power exports are expressed with a

Table 4.1: Model assumptions

	Assumptions
1	Driving and refilling of FCEVs occur within one hour time steps.
2	Driving schedules are constant for weekdays and weekends.
3	The generation of electricity from each household's PV system is the same.
4	The electricity demand from each household is the same.
5	Hydrogen produced in the wind-to-hydrogen system is transported directly to the neighborhood's central hydrogen storage without losses and is readily available.
6	The availability of water for electrolysis is not constrained.
7	Electricity consumption for water purification, compression and storage of hydrogen are ignored.
8	The preferred operating point of FCEVs as power plants is around 10kW [1]
9	Hydrogen and power can be imported. Surplus power can also be exported.
10	Whenever possible, the frequent switching on-off of FCEVs is avoided by operating FCEVs that are already switched on.

[1] Higher outputs are less efficient and not recommended in stationary mode due to thermal management needs (Lipman et al., 2004). The highest efficiency is approximately 10kW (Rodatz, Paganelli, Sciarretta, & Guzzella, 2005).

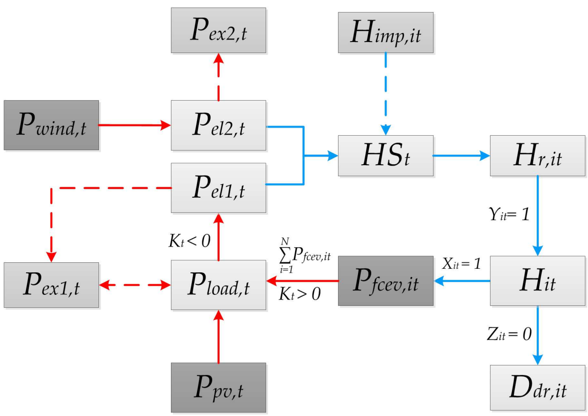


Figure 4.2: CaPP microgrid model

negative P_t^{ex1} and imports with a positive value. The number of vehicles needed when $K_t > 0$ is determined based on the preferred operating point, P_{pop}:

$$N_t^{fcev} = \frac{K_t}{P_{pop}}, N_t^{fcev} \geq 0 \tag{4.4}$$

$$P_{it}^{fcev} = \frac{K_t}{N_t^{fcev}}, \tag{4.5}$$

where N_t^{fcev} is rounded up to the nearest integer.

The power constraints are:

$$0 \leq P_t^{PV} \leq P_{max}^{PV} \tag{4.6}$$

$$0 \leq P_{fcev,it} \leq P_{fcev}^{max} \cdot x_{it} \tag{4.7}$$

$$-P_{max}^{ex1} \leq P_{ex1,t} \leq P_{max}^{ex1} \tag{4.8}$$

4.2.2. Electrolysis and hydrogen storage

Electrolysis in the wind-to-hydrogen system is defined by:

$$P_t^{wind} - P_t^{el2} - P_t^{ex2} = 0 \tag{4.9}$$

The level of hydrogen in the central storage system (HS) at time t is determined by:

$$HS_t = HS_{t-1} + (P_t^{el1} + P_t^{el2}) \cdot \frac{\eta_{el} \cdot \Delta t}{HHV} - \sum_{i=1}^{N} H_{it}^{ref} + H_t^{imp} \tag{4.10}$$

The power and hydrogen storage constraints are:

$$0 \leq P_t^{wind} \leq P_{max}^{wind} \tag{4.11}$$

$$0 \leq P_t^{el1|2} \leq H_{max}^{el} \cdot \frac{HHV}{\eta_{el} \cdot \Delta t} \tag{4.12}$$

$$HS_{min} \leq HS_t \leq HS_{max} \tag{4.13}$$

$$-P_{max}^{ex2} \leq P_t ex2 \leq P_{max}^{ex2} \tag{4.14}$$

4.2.3. Availability of FCEVs for vehicle-to-grid

FCEVs can be used for V2G ($x_{it} = 1$) based on the vehicle's location ($z_{it} = 1$), the refilling needs ($y_{it} = 0$) and the hydrogen level in the tank.

$$x_{it} + y_{it} \leq z_{it} \tag{4.15}$$

$$y_{it}, x_{it}, z_{it} \in \{0, 1\}$$

Location

The vehicles' location z_{it} is determined by the driving behavior, $D_{dr,it}$, which indicates the distance driven by vehicle i at time t. The matrix is built from statistics on daily driving distance, departure time, and arrival time. The location variable changes every time a vehicle is driving ($D_{dr,it} > 0$), therefore for a vehicle that is 'here', z_{it} will change from 1 to 0.

Refilling needs
The refilling needs of the FCEVs are determined by modeling the hydrogen tank in the vehicles. This is again determined by the driving behavior ($D_{dr,it}$), which indicates when and how much hydrogen is used for driving:

$$H_{it} = H_{it-1} + H_{it}^{ref} - \frac{P_{it}^{fcev} \cdot \Delta t}{\eta_{FC} \cdot LHV} - D_{it}^{dr} \cdot E_{fcev} \tag{4.16}$$

The constraints of the hydrogen tank are:

$$H_{i,min} \leq H_{it} \leq H_{max} \tag{4.17}$$

$$H_{i,min} = E_{fcev} \cdot D_i^{exp} \cdot sf, \tag{4.18}$$

where D_i^{exp} is the vehicle's daily expected driving distance, and sf a security factor with respect to the daily fuel needs. Refilling occurs when:

$$\text{if } H_{it-1} \leq H_{i,min} \begin{cases} y_{it} = 1 & (4.19a) \\ H_{it}^{ref} = H_{max} - H_{it-1}, & (4.19b) \end{cases}$$

with the following constraints:

$$0 \leq H_{it}^{ref} \leq H_{max} \cdot y_{it} \tag{4.20}$$

$$\sum_{i=1}^{N} y_{it} \leq N_{max}^{ref} \tag{4.21}$$

Start-up and shut-down of FCEVs
The start-up and shut-down of the FCEVs as power plants is determined using the binary variable x_{it}.

$$x_{it} - x_{it-1} = SU_{it} - SD_{it} \tag{4.22}$$

$$SU_{it} + SD_{it} \leq 1 \tag{4.23}$$

$$SU_{it}, SD_{it} \in \{0, 1\}$$

When the residual load is positive $K_t > 0$, FCEVs are used to provide power. When $K_{t-1} > 0$ and $K_t > 0$, vehicles that have been already used ($x_{it-1} = 1$) will continue to be operated whenever possible by adjusting the power to the new demand. This is to avoid switching vehicles on and off every time step, and therefore avoid unnecessary degradation due to continuous start-up and shut-down of the fuel cell. When there are no vehicles already switched on (all vehicles $x_{it-1} = 0$) or more power is needed, new vehicles will be started up.

Fair scheduling mechanism
In this model, we use a fair scheduling mechanism to start-up and operate vehicles based on the cumulative number of start-ups. Therefore, vehicles that have been used a fewer number of times will always be selected first. For each time step t, where $K_t > 0$:

- Vehicles used in the previous time step are checked, and if they are still available, they will be used again, $x_{it} = 1$.
- If more vehicles are needed, vehicle indices i are re-ordered by increasing $\sum_{t=1}^{T} SU_{it}$.
- Vehicles with the same number of start-ups are ordered following the index number i.
- The required number of additional cars are selected following said order.
- For every car, the location, refilling status, and hydrogen level are checked. If a vehicle is available, it will be started up $x_{it} = 1$.
- If there are not enough vehicles, power is imported.

4.2.4. Solar and wind generation

PV output calculation
To calculate the PV output we use eq. 4.24 as an approximation.

$$P_t^{PV} = E \cdot \eta_{PV} \cdot pf \cdot A^{pv} \cdot N_{households} \tag{4.24}$$

Where,

E**:** Hourly irradiance, $J/cm^2 \cdot h$

η_{PV}**:** Efficiency of PV panel, %

pf**:** Performance factor, %

A^{PV}**:** Rooftop surface area per household, m^2/household

$N_{households}$**:** Number of households

Wind output calculation
The wind power calculations used in this model are the equations describing an Enercon E-33 turbine using the least square technique, as presented in (Thapar, Agnihotri, & Sethi, 2011) and shown in eq. 4.25 to 4.32.

$$P_t^{wind} = 0 \qquad (for\, v < 3) \tag{4.25}$$
$$P_t^{wind} = 3.8v^2 - 17.9v + 24.5 \qquad (for 3 \leq v \leq 5) \tag{4.26}$$
$$P_t^{wind} = 6v^2 - 41v + 85 \qquad (for 5 \leq v \leq 7) \tag{4.27}$$
$$P_t^{wind} = 6v^2 - 44v + 106 \qquad (for 7 \leq v \leq 9) \tag{4.28}$$
$$P_t^{wind} = -5.6v^2 + 160.4v - 794 \qquad (for 9 \leq v \leq 11) \tag{4.29}$$
$$P_t^{wind} = -6.1v^2 + 167.5v - 811.6 \qquad (for 11 \leq v \leq 13) \tag{4.30}$$
$$P_t^{wind} = 335 \qquad (for 13 \leq v \leq 25) \tag{4.31}$$
$$P_t^{wind} = 0 \qquad (for\, v > 25) \tag{4.32}$$

4.3. Simulation Inputs

4.3.1. Input data

Data from the Netherlands was used to simulate the load pattern, PV generation, wind power generation and travel behavior of the FCEV drivers. To represent the load profiles of the 200 households, standardized profile fractions of 2014 were used (Energie Data Services Nederland (EDSN), 2013). The data was used to determine the hourly consumption throughout the year, assuming an average yearly demand of 3,400kWh. The aggregated load was obtained by multiplying by 200.

For the calculation of the PV and wind output, raw weather data from 2014 measured at a location in South-Holland by the Royal Netherlands Meteorological Institute (KNMI) was used (Royal Netherlands Meteorological Institute (KNMI), 2015). The PV generation profile was determined using the hourly solar irradiance (W/m^2) For a single rooftop PV panel, we assumed a PV efficiency of 15%, a performance ratio of 0.75, and an area of $35m^2$. We multiplied this value by the number of households, 200. Raw windspeed data (in $0.1m/s$) was used to calculate the power generated with a 335kW *Enercon* E-33 wind turbines, using the method presented in (Thapar et al., 2011). The power output was multiplied by two to estimate wind generation using two identical wind turbines with a total capacity of 670kW.

Finally, travel data from the annual report on "Research on Movements in the Netherlands"(Centraal Bureau voor de Statistiek (CBS) & Rijkswaterstaat (RWS), 2015) was used to define the driving needs of FCEVs. Using only data points corresponding to trips made by car drivers, the distribution of the following characteristics was determined for weekends and weekdays: daily distance traveled, earliest time of departure, and latest time of arrival.

Table 4.2: Input data

Variable type	Data type	Source
PV generation P_t^{PV}	Hourly data solar generation	(Royal Netherlands Meteorological Institute (KNMI), 2015)
Wind generation P_t^{wind}	Hourly data wind speed	(Royal Netherlands Meteorological Institute (KNMI), 2015)
Load P_t^{load}	Hourly data of household profile fractions	(Energie Data Services Nederland (EDSN), 2013)
Driving behavior $D_{it}dr$	Data on trip times and distances	(Centraal Bureau voor de Statistiek (CBS) & Rijkswaterstaat (RWS), 2015)

Driver data

To define the driver agent's driving schedules, we use a Dutch report from 2014 that contains data about people's daily movements (Centraal Bureau voor de Statistiek (CBS) & Rijkswaterstaat (RWS), 2015). From the initial data set, only data points that correspond to movements made by drivers are selected. We take the first departure time and latest arrival time, as the only departure and arrival times from and to their home. We take the daily distance as the total kilometers made in that day. With the data, we make three histograms shown in Fig.4.3a to 4.3c. The cumulative probabilities are used as input to generate the daily distance and the departure and arrival times for every agent.

4.3.2. System parameters

For base case simulation runs we used the input data described and system parameters shown in Table 4.3. Monthly runs were done to compare the V2G demand and power imports throughout the year, and a yearly run was done to obtain the annual performance of the microgrid and the distribution of FCEV start-ups.

Table 4.3: System parameters

Parameter	Value
N	50
H_{i0}	random from 3 to 5.64 kg
H_{max}	5.64 kg
sf	1.5
HS_0	215 kg
HS_{max}	430 kg
HS_{min}	43 kg
$H_{max}^{el1\|2}$	10.8 kg/h
N_{max}^{ref}	5
P_{pop}	10 kW
η_{el}	70% [1]
η_{FC}	60% [2]
HHV	39.4kWh
LHV	33.3kWh
E_{fcev}	0.01 kg/km

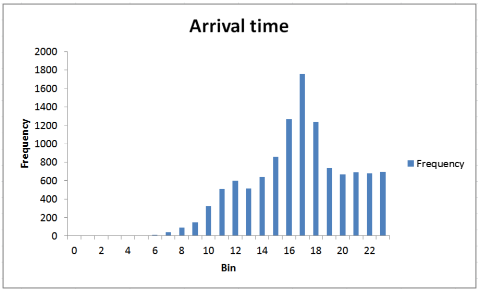
4.4. Results

In this section we present and discuss the results from the monthly and yearly simulations. Then we discuss the influence of the fair scheduling mechanism on the individual vehicles, and discuss the performance of the system and the vehicles. Finally, in the sensitivity analysis we explore some of the input parameters and their influence on the system.

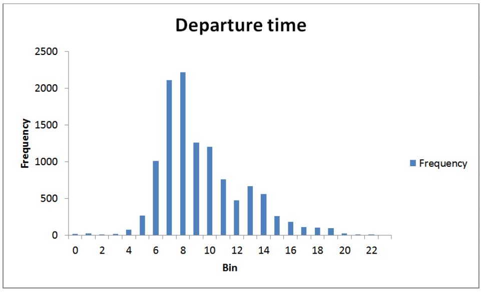
4.4.1. Yearly balance

Figures 4.4 to 4.6 show an overview of the monthly energy generation and consumption pattern. Fig. 4.4 shows the consumption of energy in the households by source: direct

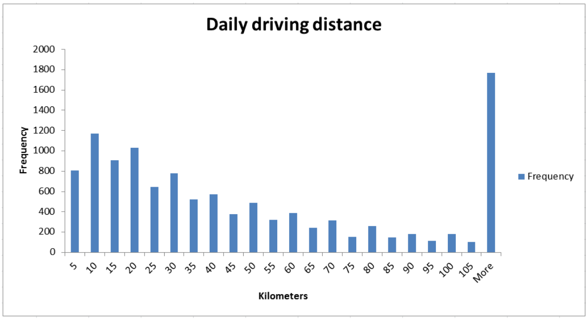
[1] Hydrogen Tools (n.d.)
[2] US department of Energy (2015)



(a) Histogram of arrival time



(b) Histogram of departure time



(c) Histogram of daily driving distance

Figure 4.3: Driving data derived from Centraal Bureau voor de Statistiek (CBS) and Rijkswaterstaat (RWS) (2015)

PV, vehicle-to-grid and imports. In most of the months, but especially in winter, more than half of the energy consumption is covered by vehicle-to-grid. Only in the winter months electricity is imported. In Fig. 4.5a a clear monthly trend in PV generation is observed. However, the direct household consumption remains relatively constant. The rest of the solar energy produced is used for electrolysis or is exported. Due to the low PV generation in the winter months, the amount of hydrogen produced from surplus PV generation is only significant from March to September. Fig. 4.5b shows the wind generation and consumption throughout the months. Although there is no clear trend in the amount of energy generated every month, more hydrogen is produced via electrolysis in the winter months.

Finally, Fig. 4.6 shows the monthly production and consumption of hydrogen. Both production and consumption follow a seasonal trend – being highest in the colder months and lower in the summer months. As these figures show, the microgrid depends much on vehicle-to-grid in order to use as much energy generated locally as possible. The amount of V2G produced is influenced by the number of FCEVs in the system, which was assumed to be 50. Although most of the energy consumption is either from PV or V2G, a lot of the PV and wind generated is exported. Although we have assumed there are no constraints in exporting power from the microgrid, if necessary this could be reduced by increasing the hydrogen storage and/or the electrolyzers' capacity. However, the sizing of the system components is not the main goal of this exercise.

Table 4.4 shows the yearly balance of electricity generation, consumption, and exchanges with the grid. Very little power is imported during the year, whereas exports exceed the yearly consumption.

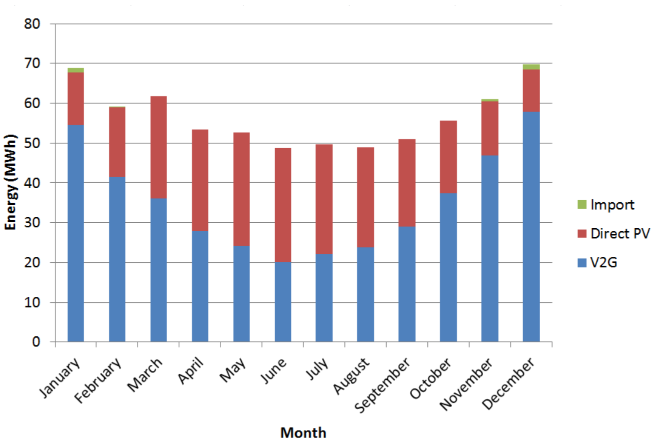
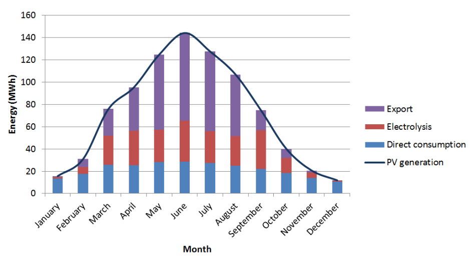


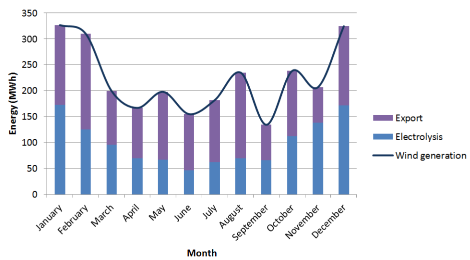
Figure 4.4: Monthly household consumption by generation type

Table 4.4: Yearly balance, electricity generation and consumption in MWh

Renewable generation	Vehicle-to-grid from FCEVs	Electricity imported	Total Supply
3,548.07	413.73	2.28	3,972.08
Household consumption	**Electrolysis**	**Electricity exported**	**Total Demand**
680.01	1,368.52	1,923.55	3,972.08



(a) Solar PV energy



(b) Wind energy

Figure 4.5: Monthly generation and consumption of renewable energy

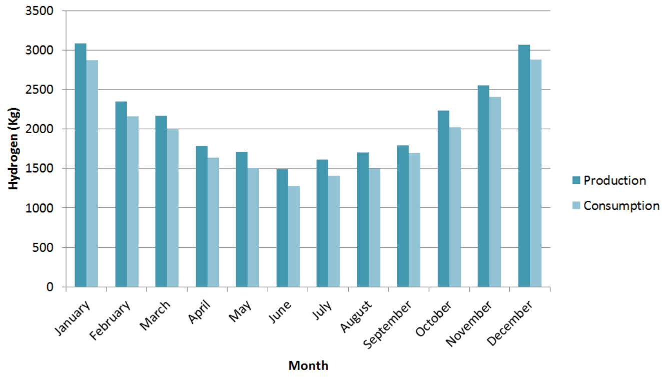


Figure 4.6: Monthly production and consumption of hydrogen

4.4.2. Fair scheduling

The distribution of total start-ups per car at the end of a yearly simulation run (Fig.4.7) shows that most of the cars are used between 155 and 164 times per year. On average, every car is used 159 times during the year, i.e. around 3 times per week. The distribution has a bell-shaped curve, with few outliers. The reason for the relatively low number of start-ups of two vehicles is their low daily driving distance: one car drives 5 km every day, and the other one drives 5 km in weekdays and 15 km in weekends. This causes the minimum hydrogen requirements to be very low. As a result, the car might be able to drive many days without refilling, but often it is not available for power generation due to the insufficient level of hydrogen for vehicle-to-grid.

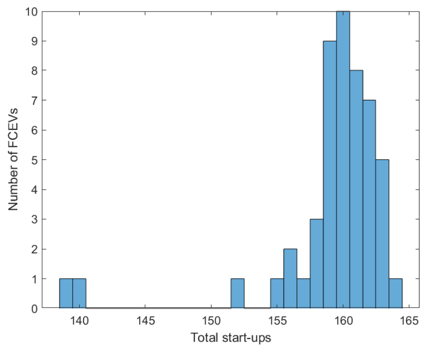


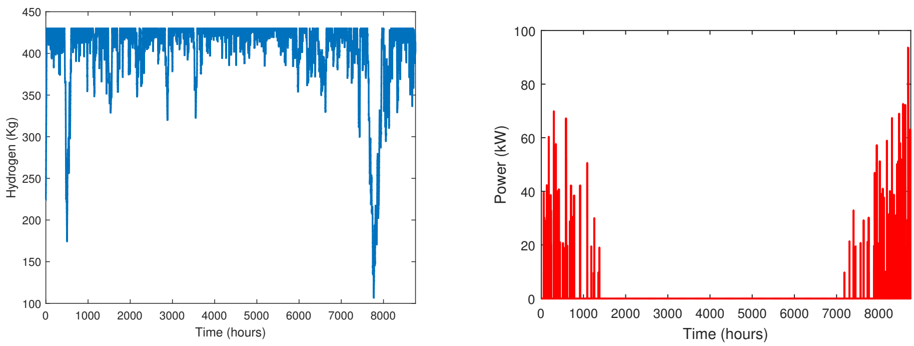
Figure 4.7: Yearly distribution of start-ups

4.4.3. Performance

Monthly simulation runs show the trend in V2G supplied (MWh) per vehicle, and number of start-ups in different seasons. As indicated in Table 4.5 the system performance and implications for drivers fluctuate throughout the months of March,

Table 4.5: System performance and implications for drivers

Month	System performance		Implications for individual drivers (average)						
	V2G, MWh	Self supply, %	V2G, MWh		Start-ups		Available hours		Capacity factor, %
			mean	s.d.	mean	s.d.	mean	s.d.	mean
March	54.45	100	0.72	0.24	13.52	0.54	12.38	3.38	18.8
June	27.98	100	0.4	0.11	7.86	0.35	14.14	3.29	9.47
September	22.20	100	0.58	0.17	10.48	0.5	12.86	3.37	15.03
December	37.30	98.2	1.16	0.48	22	3.02	9.76	3	38.26
Year	421.73	99.67	8.43	2.50	159.22	4.65	12.11	3.11	19.14



(a) Hydrogen level in the refilling station (b) Power imports

Figure 4.8: Hydrogen level and power imports throughout the year

June, September and December. The residual demand in the system influences the number of start-ups: June and December being the months with lowest and highest start-ups per car, respectively.

At the system level, the self-supply capability of the microgrid depends on the generation of renewable electricity and the fuel cell vehicles. In the summer months, the cars in the microgrid are enough to supply 100% of the microgrid's demands. In winter, however, the vehicles are not enough to achieve the same reliability levels and power has to be imported. For the cars, this means that their use for vehicle-to-grid increases in the winter months. Under the assumptions used in the model, cars are available whenever possible, but this is affected by the demand for V2G. A higher residual demand reduces the number of available hours, since more fuel is used for V2G. When all cars are available under the same conditions, they are used on average 19% of the available time throughout the year to achieve the indicated self-supply levels.

As shown in Fig. 4.8a hydrogen does not need to be imported throughout the year, and therefore a storage capacity of 430kg is sufficient for the system described in this paper. Power imports are required in January and February, and from October to December, as depicted in Fig. 4.8b. January and December are the months in which PV generation is most insufficient.

4.4.4. Sensitivity analysis

In this section we perform a sensitivity analysis on some of the input parameters used in the simulation, namely the safety factor used to calculate fuel needs, the number of cars int he system, and the initial fuel level of the vehicles.

Safety factor for expected fuel needs

The fuel safety factor (sf) is the value used to calculate the daily hydrogen needs for driving H_{it}^{min} (See eq.4.18), which influences the availability of vehicles for V2G. For each vehicle the minimum hydrogen needs are defined by the hydrogen consumption estimated for the daily driving distance, multiplied by a fuel safety factor. In the simulation, this factor was set to 1.5. For the sensitivity analysis we vary the safety factor from 1.5 to 1 and 2 (+/- 40%) to determine how much it affects the aggregated availability of FCEVs. From the perspective of an individual vehicle, a lower sf will allow each car to be used for longer until lower fuel levels, and a higher sf will limit the use of vehicles, due to the increased H_{it}^{min}.

Table 4.6: System performance and implications for drivers: Safety factor for fuel needs

sf	**System performance**		**Implications for individual drivers (average)**						
	V2G, MWh	Self supply, %	V2G, MWh		Start-ups		Available hours		Capacity factor, %
			mean	s.d.	mean	s.d.	mean	s.d.	mean
1	421.45	99.62	8.43	2.38	157.1	3.85	12.3	3.05	18.84
1.5	421.73	99.67	8.43	2.50	159.22	4.65	12.11	3.11	19.14
2	421.13	99.58	8.42	2.50	162.62	5.67	11.79	3.07	19.64

The results in Table 4.6 show that on the aggregate level, there is little difference in the system performance. The self-supply percentage stays between 99.58% and 99.62%, although the volume supplied and self-supply percentage are clearly highest when the sf value is lowest, 1. There are, however, more notable differences in the implications for drivers. The average number of start-ups decreases to 157.1 for the lower value and increases to 162.62 to the higher sf value. The same happens with the capacity factor. This is because when cars have a lower sf, they can be used longer, reducing the need to start up additional cars. When the sf is higher, vehicles that are being used have to be shut down earlier, which requires starting up additional cars. Therefore, the average use (capacity factor) of each vehicle increases in order to supply the residual load.

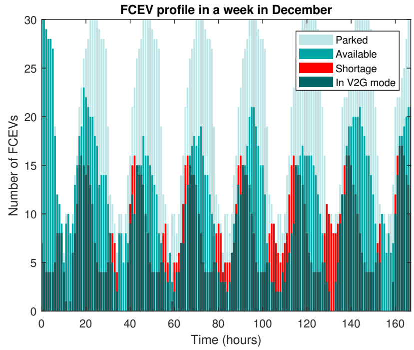
Number of FCEVs

In the model, there are 50 FCEVs that can be used to supply vehicle-to-grid. The number of FCEVs influences directly the availability of resources for meeting the residual demand. To analyze to what extent a large change in the number of FCEVs can affect the system performance and the participation of FCEVs, we reduce and increase this number by 40%, to 30 and 70 vehicles.

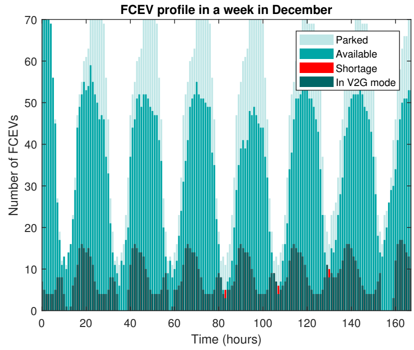
Table 4.7 shows the results of these two runs. There is a significant difference in the system performance and implications for drivers when the number of FCEVs is 30. However, with 70 vehicles the difference is much smaller as the self-supply percentage only increases by 0.3%. With 30 vehicles, the use of the vehicles increase from 19.14 to

Table 4.7: System performance and implications for drivers: Number of FCEVs

FCEVs	**System performance**		**Implications for individual drivers (average)**						
	V2G, MWh	Self supply, %	V2G, MWh		Start-ups		Available hours		Capacity factor, %
			mean	s.d.	mean	s.d.	mean	s.d.	mean
30	405.91	97.34	13.53	4.77	242.03	10.35	11.51	2.34	32.32
50	421.73	99.67	8.43	2.50	159.22	4.65	12.11	3.11	19.14
70	423.83	99.97	6.05	1.77	118.47	3.7	12.53	3.21	13.28



(a) 30 FCEVs



(b) 70 FCEVs

Figure 4.9: Hourly profile of FCEVs throughout a week in December

32.32%, which means that cars are used a third of the time when available. However, the self-supply percentage is reduced by about 2% and the total V2G supplied by 15 MWh. When 70 FCEVs are used in the model, the capacity factor of the vehicles is reduced to 13.28% while providing an aggregated 2 MWh more throughout the year. Therefore, having fewer vehicles has more significant negative effects than increasing the number of vehicles. If increased, nevertheless, the requirements for the vehicles are reduced while increasing the system performance.

The effect on the number of vehicles becomes more visible when comparing the hourly FCEV profile throughout a week in December. In Fig.4.9a and Fig.4.9b we show the number of FCEVs parked, available for V2G, in V2G mode for every hour in a week. The hours in which the available vehicles are insufficient, the shortage is shown in red.

Initial fuel level

Additionally, we also explore the effect of the initial fuel level of the vehicles, H_{i0}. In our simulation, the initialization of the fuel level for each vehicle was defined randomly between 3 and 5.64 kg. This means that at the beginning, the FCEVs tanks are at least 50% full. This influences the fuel level in the following time steps and in turn the availability of vehicles for V2G. Figure 4.11a shows the FCEV profile for a week in December, with lower initial fuel tank levels (1 to 3 kg). Figure 4.10 shows the FCEV profile for a week in December, with the base case initial fuel tank levels. Finally, Fig. 4.11b shows the FCEV profile for a week in December, when all vehicles start with the maximum fuel tank level, 5.64 kg.

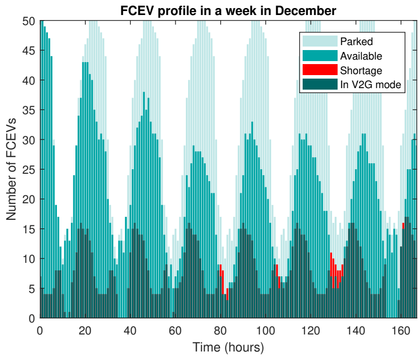


Figure 4.10: Hourly profile of FCEVs throughout a week in December - base case

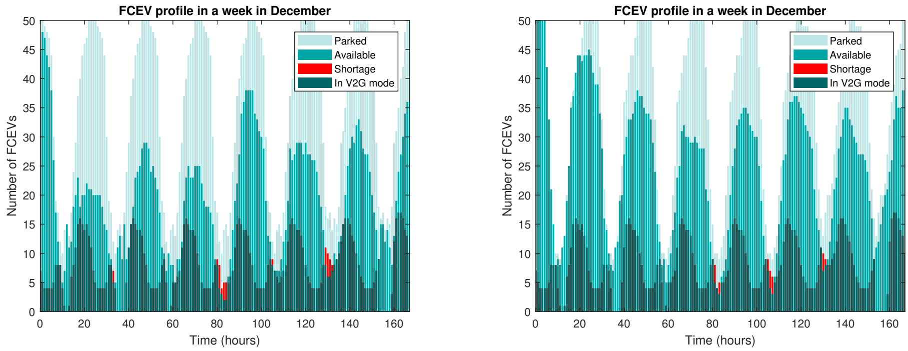
The results show that the initialization of the fuel level affects the availability of vehicles in the following time steps. In Fig. 4.11a, the availability after a day of driving is reduced to less than half of the vehicles. After some hours, however, the availability increases again as vehicles refill their tanks. In the base case, Fig.4.11a, availability is only reduced to 40-45 vehicles, similarly to the initialization with maximum fuel level in Fig.4.11b. The availability is a bit more stable in the base case and maximum fuel level scenario, as the highest availability stays between 30 and 35 after two days. With the lower initial fuel scenario, the highest availability fluctuates between 25 and 35 after two days.

4.5. Discussion

With the system characteristics and the size of the different components we see in the yearly balance that a large part of the electricity generated from PV and wind is exported and not used for electrolysis. The exports are influenced by the percentage of direct PV consumption as well as the electrolyzers' capacities and the hydrogen storage capacity. We assumed there were no constraints for exporting and that this would be a possible business case for a microgrid in a situation where the first goal is self-supply of energy. While the goal of this model was to understand the operation of a CaPP microgrid system, it would be possible to further analyze the appropriate system sizing based on costs. This would depend much on the ownership structure of the microgrid.

Some of the parameters used were analyzed to observe the sensitivity of the results to the specific values used. The safety factor (sf) used to calculate the expected fuel needs was first tested. There was not much difference in terms of the system performance. For the drivers, however, there was some difference in the average number of start-ups and the capacity factor. A higher safety factor leads to cars being started-up and shut-down more often to achieve a similar self-supply percentage. Surprisingly, even with small differences, when using both a lower and higher safety factor the total V2G supplied and self-supply percentage are lower than when it was 1.5.

The number of FCEVs in the system affects the results significantly, especially in



(a) Lower initial fuel, 1 to 3 kg

(b) Maximum initial fuel, 5.64 kg

Figure 4.11: Hourly profile of FCEVs throughout a week in December

terms of the implications for drivers. With 30 FCEVs, cars have to supply on average more energy and are started-up more often (4.6 times/week). With 70 FCEVs, the average use of FCEVs decreases and cars are only used about 2.3 times/week. At the system level, although more cars increase the system performance, using 70 cars only increases the self-supply by 0.2%. The figures with the FCEV profile in a week in December show that not only the number of FCEVs is important, but also the timing of their availability – which has to match the V2G demand profile. With 70 FCEVs, there is still shortage of cars at certain moments even when there are enough FCEVs parked.

A number of other assumptions were used when building and running the model. The sizing of all the components as well as the configuration of the system can have consequences on the results of the simulation. On the one hand, reducing the over-sized renewable generation capacity could reduce the exports at the expense of possibly a lower system performance. Changing the hydrogen conversion and storage size would be a different way to cope with the large exports of wind and PV generation. On the other hand, the wind turbines are assumed to be used exclusively for hydrogen production. This is because it is assumed that wind turbines will not be placed near the microgrid. However, if wind energy could be used for household consumption, the demand for V2G would change, as well as the system performance. If necessary, the implications for FCEV drivers under different system configurations could also be explored. In terms of the data used, the renewable generation and household load used as inputs were only for a certain year. Given the seasonal differences observed in the results, the use of several other years would lead to different results in the system performance and implications for drivers. The driving schedules used for the FCEVs were constant for weekdays and weekends, and do not include any unexpected additional trips. A stochastic more driving behavior would definitely influence the plug-in times as well as fuel availability. Our focus is more on the energy part of the system, but the transport behavior could be further explored to answer different types of research questions.

4.6. Conclusions

In this chapter, we presented a model implemented in Matlab to simulate the operation of a Car as Power Plant microgrid, where FCEVs are used for vehicle-to-grid. The results show that while the microgrid can almost supply 100% of the household demand using locally generated energy (PV or V2G), the self-supply percentage varies throughout the months. As the main source is solar energy, the output in the rooftop PV panels and the household load profile determine the demand for vehicle-to-grid. As a result, the capacity factor of FCEVs changes throughout the year, leading to big differences between summer and winter months. The average number of start-ups in different months also changes. While on average cars are started-up about 3 times per week during a year, these requirements actually vary every month. Using a fair scheduling mechanism to decide which cars to start-up, we observe that at the end of a year most of the cars have a similar number of start-ups. As the start-up and shut-down processes can be linked to the degradation of fuel cells, this can be used as a measure to achieve a more even distribution in the use of FCEVs for V2G.

The results of this chapter demonstrate the importance of FCEV availability in the operation of a Car as Power Plant system. We observed that both the number of vehicles and the fuel available for V2G influence the system performance and the requirements from individual vehicles. While higher reliability levels can be reached by simply adding more vehicles, the conditions under which each vehicle participates will eventually determine the system's performance. Therefore, more insights are needed on how the power from individual vehicles can be leveraged. In this model, it was assumed that all vehicles participate equally and this leads to loss of autonomy, since vehicles are available but not used for a large portion of the time. In our model, we characterized the availability of a vehicle using three physical conditions that should be fulfilled together. To be available, a FCEV must 1) be parked, 2) not be refilling, and 3) have sufficient fuel. However, from a socio-technical system perspective, vehicle availability is not only constrained by physical conditions but also by the action of involved actors. The rules to guide and constrain these actions are further explored in the next chapters.

5

Contracts for vehicle-to-grid transactions

5.1. Introduction

This chapter is focused on the research sub-question *"What rules can be used to manage vehicle-to-grid in Car as Power Plant systems?"*. As shown in Fig. 2.5, it represents the last contribution to the conceptualization of CaPP systems as socio-technical systems, and is focused on the rules needed for vehicle-to-grid operation. Using the lessons in the previous chapters, we present three contract types for vehicle-to-grid, which provide different sets of rules for drivers and aggregators. First, we discuss vehicle-to-grid as a flexibility source and how it relates to the market coordination mechanism for flexibility trading. Then, we discuss the need for diverse contract types for different markets and heterogeneous drivers, and propose a classification of contracts based on demand response literature. We explain the differences between them from a socio-technical system operation perspective and discuss the parameters in each contract type.

5.2. Flexibility trading and vehicle-to-grid

The Universal Smart Energy Framework (USEF) defines the relationships in flexibility trading using prosumer-side resources (USEF Foundation, 2017). Since electric vehicles and FCEVs can be considered prosumer-side flexibility resources, the framework can also be used to describe the V2G value chain, as shown in Fig. 5.1. Drivers provide V2G to the electricity system via an aggregator, who may interact with balance responsible parties (BRP), the Transmission System Operator (TSO) and/or the Distribution System Operator (DSO) for the supply of V2G in different markets. The literature on vehicle-to-grid is more focused on the relationships and interactions between Aggregator and flexibility buyers than on the interactions between drivers and the Aggregator.

Parts of this chapter have been published in (Park Lee, Lukszo, & Herder, 2018). The work was devised, conceptualized and executed by Park Lee.

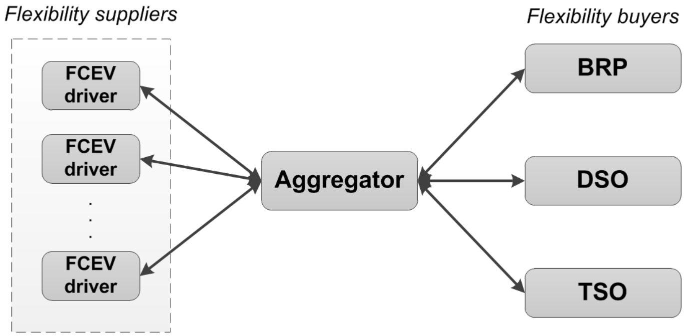


Figure 5.1: Relationships of actors in the V2G value chain, based on USEF Foundation (2015)

Figure 5.2: USEF market coordination mechanism. Source: USEF Foundation (2015)

As Fig. 5.2 shows, the framework also proposes a market coordination mechanism for flexibility trading that consists of five stages. The Contract phase is where agreements between prosumer and aggregator regarding the capacity available and the conditions for activation are defined. In the Plan and Validate stages, the aggregator makes plans for energy supply and demand, and these are validated if feasible. The Operate stage refers to the dispatch of resources. Transactions are finalized in the final Settle phase.

The same mechanism would be used to trade the power of EDVs or FCEVs in electricity markets. In terms of this market coordination mechanism, the V2G literature is more focused on the Plan and Operate stages when exploring EDV participation in electricity markets (Broneske & Wozabal, 2017; Sortomme & El-Sharkawi, 2011, 2012). There is limited knowledge, thus, on how the Contract phase affects the further stages.

5.3. Need for diverse vehicle-to-grid contract types

For all types of markets and services, the supply of V2G has different characteristics. As Broneske and Wozabal (2017) concluded, in markets with different 'energy throughput' characteristics, different contract parameters are suitable and thus valuable for the aggregator. Kempton and Tomić (2005a) also suggest that when providing ancillary services the availability (capacity) is more valuable than the actual energy supplied. Even when drivers suffer losses from selling electricity, capacity payments sufficiently make up for the costs incurred (Kempton & Tomić, 2005a). Since the characteristics for participation in V2G differ in each market and system, different types of rules would be needed to make sure the needs in each system are met.

In the demand response (DR) literature, demand response programs can be categorized into 'explicit' (volume-based) and 'implicit' (price-based) mechanisms (Smart Energy Demand Coalition, 2015). The first one refers to explicitly defining the level of flexibility to be activated, and is appropriate for system reliability purposes. The latter refers to the reaction of consumers to prices and thus the provision of flexibility without a previous agreement on the volume (Koliou, 2016). He et al. (2013) emphasize the importance of *activating* consumers for demand response to be successful. To achieve this, the authors present different types of contracts that can be suitable for consumers with distinct technical capabilities and preferences, as shown in Table 5.1. In terms of the signal form, the contracts can be divided into *price-based*, *volume-based*, and *control-based* contracts, all of which have different technical characteristics and high level implications for prosumers.

The concepts from demand response can be extended to V2G, although there are fundamental differences between DR and V2G. In the case of DR, the service is a deviation of the normal consumption pattern, usually provided through household load or EV charging. Vehicle-to-grid on the other hand, implies allowing the use of a vehicle as a dispatchable generation unit. Demand response and vehicle-to-grid are two distinct ways to increase flexibility in electricity systems through prosumers (Holttinen et al., 2013). The concepts discussed by He et al. (2013) and the DR literature can be used as guidelines to define different ways in which the V2G service can be activated.

Currently there is no distinction of contract types in the vehicle-to-grid literature. The only form of contract proposed is defined by the plug-in time (timing and duration) and guaranteed driving range after V2G (Broneske & Wozabal, 2017; Guille & Gross, 2009; Parsons et al., 2014). Freeman et al. (2017) explore different strategies for V2G participation with BEVs in the wholesale market. One of them allows the driver to define a selling price for V2G, leading to the lowest battery cycles and highest savings (net profits) when compared to other strategies where the driver does not control the minimum price. Although the aggregator's role is implied, there are no details about the contractual relationships and there seems to be no profit sharing with the aggregator. This example demonstrates that when participating in the electricity market, allowing drivers to set a minimum price for activating V2G would help them control the level of expected revenues and thus make participation more attractive.

In conclusion, there is still a limited focus in the literature on V2G contracts and their influence on system operation. From a socio-technical system perspective, the interactions in the supply-side of the vehicle-to-grid value chain (Fig. 5.1) and the influence of the Contract phase on the subsequent phases (Fig. 5.2) deserve more attention. For aggregators to sell V2G power in different markets, the contract parameters used to coordinate drivers must be aligned with the characteristics of both individual drivers and the markets, as demonstrated in the DR literature. Therefore, there is a need to define different types of vehicle-to-grid contracts and to explore their influence on the operation of future electricity systems.

5.4. A classification of vehicle-to-grid contracts

In this section we present three contract types for vehicle-to-grid with FCEVs. First, we analyze the V2G operation of a single vehicle and identify the conditions and constraints to be incorporated in vehicle-to-grid contracts: time and energy available, activation criteria, and remuneration. A classification of different contract types for vehicle-to-grid is proposed, inspired by contracts from the demand-response literature (He et al., 2013; Smart Energy Demand Coalition, 2015). The contract parameters are defined using the conditions of V2G operation discussed in this section and explored in (Freeman et al.,

Table 5.1: Demand response contract types. Source: He et al. (2013)

Contract type	Technical features		High-level terms				
	Signal form	Signal volatility	Price risk	Volume risk	Complexity	Autonomy loss	Financial compensation
TOU pricing	Price-based	Static	Low	None	Low	None	Limited
Dynamic pricing	Price-based	Dynamic	High	None	High	None	High potential
Fixed load capping	Volume-based	Static	None	Low	High	Limited	Limited
Dynamic load capping	Volume-based	Dynamic	None	High	High	Limited	High potential
Direct load control	Control-based	Predefined	None	None	None	High	Limited/High potential

2017; Guille & Gross, 2009; Parsons et al., 2014) and (Park Lee & Lukszo, 2016).

5.4.1. From vehicle-to-grid operation to contract types

Based on the model presented in Chapter 4 we analyze the possible states of a vehicle in a Car as Power Plant, as the flowchart of part of the model algorithm in Figure 5.3 shows. The rest of the model algorithm is not shown, as we focus on how the vehicle states change. A car drives twice a day, in and out of the CaPP microgrid. When it is *here*, i.e. in the microgrid ($z = 1$), the hydrogen level is checked. If it is lower than or equal to the minimum hydrogen needs for driving, it is refilled ($y = 1$), increasing the level of hydrogen. Whenever the hydrogen level is higher than the minimum, it is considered to be available. Indicated in blue, when there is V2G demand, the controller decides which available vehicles to operate ($x = 1$). When used for vehicle-to-grid, hydrogen is used from the vehicle's tank, depending on the amount of electricity supplied $P_{it}^{fcev} \cdot \Delta t$. After V2G operation, if the car is still *here* and has enough fuel, it is still considered to be available for vehicle-to-grid.

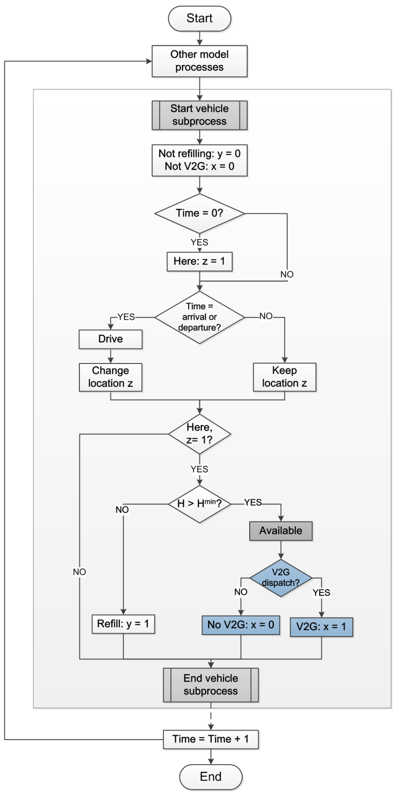


Figure 5.3: FCEV states in vehicle-to-grid operation as modeled in Chapter 4

Figure 5.3 reflects the underlying assumptions used in Chapter 4. Plug-in behavior is not explicitly modeled, and vehicles are available at all times when they are in the

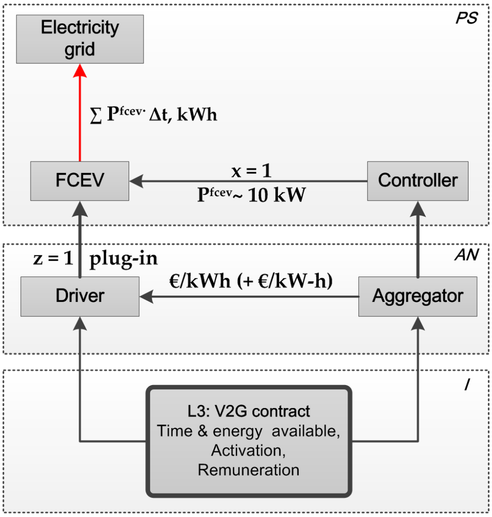


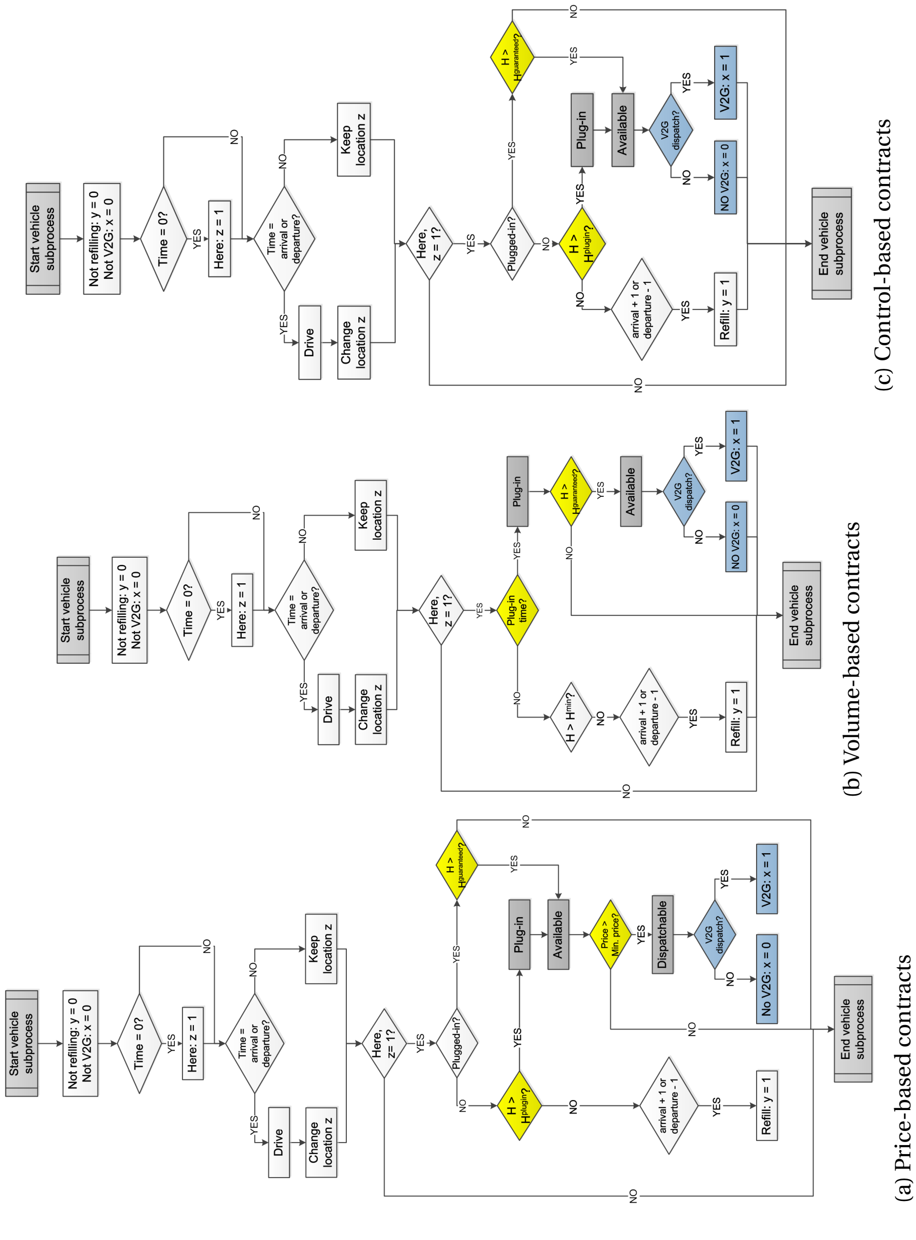
Figure 5.4: Single-vehicle V2G operation from a socio-technical system perspective

Table 5.2: Vehicle-to-grid contract concepts

Conditions and constraints		Vehicle-to-grid contract types: Price-based	Volume-based	Control-based
Time	$z = 1$ + plug-in	Plug-in duration	Committed plug-in time	Plug-in duration
Energy	$\sum_{t=0}^{23} P_{it}^{fcev} \cdot \Delta t$, kWh	f(Fuel at plug-in)	Committed amount	f(Fuel at plug-in)
Activation	$x = 1$	Price	Demand	Demand
Remuneration	€/kWh (+ €/kW-h)	Energy	Energy + capacity	Energy + capacity

microgrid and have enough fuel. When considering the V2G operation from a socio-technical system perspective, we can identify the actors' actions and decisions on the physical system. Fig. 5.4 shows the relationships between the physical system (*PS*), actor network (*AN*) and institutions (*I*) in the V2G operation. A car, thus, is owned and used by a driver. He or she decides when to use it for driving and when to connect the vehicle to the grid. The aggregator makes decisions through the controller to use the available FCEV for vehicle-to-grid. In this transaction, the aggregator pays for the energy used (and the capacity, depending on the case). This perspective shows that for a car to be available, it does not only have to be *here*, but it also requires the driver to follow with a *plug-in* action. Moreover, the availability, is constrained by the amount of energy/fuel available to the aggregator.

From the technical aspects of V2G operation and the literature we define the minimum conditions that have to be agreed in a vehicle-to-grid contract, between driver and aggregator: Time and energy available, activation criteria, and remuneration. Based on the classification of DR types, we propose three V2G contract types: price-based, volume-based and control-based contracts. Table 5.2 shows an overview of the contracts, which consist of different rules that define vehicle-to-grid participation. The



(a) Price-based contracts

(b) Volume-based contracts

(c) Control-based contracts

Figure 5.5: FCEV states in vehicle-to-grid operation with different contracts

time availability indicates when a vehicle will be plugged in. The energy availability indicates how much energy can be used by the aggregator in a day, once a car is plugged in. The activation indicates the signal type, which defines the operational rule for vehicle-to-grid supply. The remuneration indicates whether a driver is remunerated only for the energy provided or also for the capacity provided.

With price-based contracts drivers can define the minimum price they want for the car to be used. Their vehicle is available for V2G for the time the vehicle is plugged in and until the guaranteed fuel level is reached. Therefore, once they plug-in the energy available is defined by the fuel at plug in and the guaranteed fuel level. When the market price is higher than the minimum price, a car is considered to be dispatchable. The remuneration is based on this minimum price.

With volume-based contracts, drivers commit to having a certain amount of energy available during a given time interval. This means that they have to be plugged in during that interval, and after the agreed time, even if plugged in the car is not available to the aggregator. If the committed volume has been used by the aggregator, the car is not available even if it is within the committed time interval. In this case, usually, the aggregator will activate V2G based on the V2G demand signal. Because of the commitment of energy and time, the aggregator may provide a capacity payment as well.

With control-based contracts, drivers are available for the time they are plugged in, similarly to the price-based contracts. The amount of energy available also depends on the amount of fuel at plug-in and the guaranteed fuel level. In this case, V2G may be activated based on the system needs. The remuneration also has a capacity component. While there is no commitment, capacity payments can be used to reward availability.

The implications of the different contract types are depicted in in Fig. 5.5, which shows only the subprocesses that are relevant to the vehicle states. As the figure shows, for a car to be available, a plug-in step is required first, which is not considered in Fig. 5.3. The new conditions related to contract parameters are indicated in yellow. Indicated in blue again, the control on the fuel cells for vehicle-to-grid operation depends on the microgrid operator or aggregator.

Although the contracts parameters were defined for FCEVs, they could be used also for plug-in EVs. Although the coordination of smart charging with plug-in EVs can also be arranged through contracts with an aggregator, V2G refers strictly to the power flows from vehicle-to-grid. For the implementation of combined smart charging and vehicle-to-grid (charging and discharging) with battery EVs, we suggest adding contract parameters to provide the appropriate limits to use the battery.

5.4.2. Price-based contracts

Price-based vehicle-to-grid contracts involve a price signal for the activation of V2G. As shown in Table 5.3, the driver defines a minimum price he wants to receive for V2G. Therefore, the aggregator will use the vehicle only when he can provide this remuneration (e.g. market price is higher) and as long as there is enough energy in the vehicle. The availability, or times at which the FCEV is plugged in is voluntary and therefore not committed. Depending on the market, the aggregator may define a remuneration structure such that the driver gets the minimum price and a percentage of the additional profit (market price – min. V2G price). This percentage could depend on

Table 5.3: Price-based contract parameters

Contract parameter	Description
Min. V2G price	Minimum price for activation, defined by driver
Guaranteed fuel level	Minimum level of fuel guaranteed after operation
V2G remuneration	Remuneration for energy supply, e.g. min. V2G price

the available energy at plug-in, or the plug-in duration so that availability is rewarded.

This type of contract could be used for drivers to participate in the wholesale market, where average prices may not be high enough but peak prices can make V2G profitable (Freeman et al., 2017).

5.4.3. Volume-based contracts

Volume-based contracts involve commitment of a predefined volume of energy within a certain time interval, as shown in Table 5.4. Drivers can limit the amount of energy they are willing to provide (maximum volume). Since the fuel capacity in the FCEV tank is limited, this means that FCEVs need to have a certain amount of volume at plug-in. By defining the guaranteed fuel level, the fuel amount required at plug-in can be calculated to help drivers comply with the commitment. These contracts can be attractive for drivers that have a very predictable driving schedule and can be plugged in regularly, for example at the workplace parking facilities or at home. This type of contract can be used when the commitment of availability and energy is important, such as in local energy systems depending on variable RES and FCEVs (Oldenbroek et al., 2017; Park Lee & Lukszo, 2016; Shinoda, Park Lee, Nakano, & Lukszo, 2016) or when providing reserve capacity. Since there is a commitment on the time and volume, the remuneration structure could be designed such that the commitment is rewarded.

Table 5.4: Volume-based contract parameters

Contract parameter	Description
Time interval	Time interval (start + duration) for availability
Max. Volume	Maximum volume usable for V2G
V2G remuneration	Energy and capacity remuneration
Guaranteed fuel level	Minimum level of fuel guaranteed after operation
Min. fuel required at plug-in	Calculated level of fuel required in the vehicle before plug-in

5.4.4. Control-based contracts

With control-based contracts the driver cedes control over to the aggregator as soon as the car is plugged in. The availability is defined by the time interval, which could be pre-committed or informed at plug-in by indicating the expected departure time. As shown in Table 5.5, the activation criterion is defined by the guaranteed fuel level to be left after V2G. Although it is similar to the volume-based contract, there is no commitment on the maximum volume available. Implicitly, it is defined once the car is plugged in, by the initial level of fuel and the guaranteed fuel level. However, the total available volume can change every time. This may be the contract form with lowest complexity and in the absence of a time interval commitment, it gives freedom to the driver to plug-in anytime. However, when plugged in, the driver cannot limit how much energy may be used by the aggregator. High levels of availability or fuel levels may be incentivized by designing V2G remuneration structures that consist of a V2G tariff plus a capacity remuneration that is linked to the time duration and the fuel level at plug-in.

Table 5.5: Control-based contract parameters

Contract parameter	Description
Time interval	Plug-in time (voluntary or pre-committed)
V2G remuneration	Energy and capacity remuneration
Guaranteed fuel level	Minimum level of energy guaranteed after operation

This type of contract is in practice implied in the assumptions made in the microgrid in (Park Lee & Lukszo, 2016), where all FCEVs are assumed to be plugged in whenever they are in the neighborhood and the controller can use them until the minimum fuel level is reached. It is also similar to the V2G contracts in the literature (Broneske & Wozabal, 2017; Guille & Gross, 2009; Parsons et al., 2014). Control-based contracts could be attractive in cases when vehicle availability is high without commitment, e.g. large fleet of FCEVs that are usually plugged in at regular times, and/or when volume commitment beforehand is not necessary because it is not scheduled ahead.

5.5. Conclusions

In this chapter we presented three explored the rules needed to mange vehicle-to-grid in CaPP systems. Using a socio-technical system operation perspective, a vehicle-to-grid transaction was described as a set of actions and decisions that the driver makes regarding the vehicle, and the decisions made by the aggregator to operate it. We derived the key types of rules needed to make agreements on V2G operation: time and energy availability, activation criteria and remuneration. Based on the demand response literature, we defined three contract types: price-based, volume-based and control-based contracts. Each consist of a different set of rules regarding vehicle-to-grid operation. Therefore, each contract type is more suitable for certain CaPP systems and can be used to engage prosumers with different needs and preferences.

A quantitative analysis is needed to better understand the role of different contracts in guiding the interactions between drivers and the aggregator, as well as the effects of the *Contract* phase on the further stages of the market coordination mechanism defined by USEF. The role of these contracts is further analyzed in the next two chapters, through agent-based modeling and simulation.

6

CaPP microgrid: Volume-based and control-based contracts

6.1. Introduction

In this chapter we address the last research sub-question: *"How do different contract types and rules affect the operation of vehicle-to-grid in CaPP systems?"*. After having conceptualized contract types for V2G in Chapter 5, we move on to their formalization in models, to investigate the effect contracts on CaPP systems. As discussed in Chapter 2, this involves formalizing CaPP systems as socio-technical systems in an agent-based model, and explicitly modeling contracts in relation to actors' actions and the physical system operation.

To explore the effect of contract types on CaPP systems, in this chapter we continue exploring the CaPP microgrid. We investigate volume-based and control-based contracts, which would be suitable ensuring a high level of availability to cope with the variable residual demand. Volume-based contracts consist of a time and volume commitment from drivers, while control-based contracts allow aggregators to use as much energy as possible whenever a car is plugged in.

While the type of contract can have an important effect on the system, additional conditions and constraints in the contracts offered by the aggregator can further influence the system operation. Therefore, the specific goal of the CaPP microgrid agent-based model is to explore how contract types and implementation strategies influence the system operation. Given the seasonal changes in the local residual demand seen in Chapter 4, we compare seasonal vs. fixed volume-based contract implementations, as well as seasonal vs. flexible control-based contract implementations. To compare the performance of these contracts, we propose a comprehensive multi-criteria assessment based on three types of criteria: reliability, economic performance and driver autonomy. These take into account the system performance at the aggregate level as well as the individual participants' performance.

The chapter is structured as follows: first, we introduce the CaPP microgrid as a socio-technical system. We describe the physical system, the main actors and the institutions in place. Then, we describe how the concepts are used to formalize and build an agent-based model. We present the results of the simulation runs and provide a discussion of the results.

6.2. System description

6.2.1. Physical system

The physical system is depicted in Fig. 6.1, and is based largely on the CaPP microgrid system modeled in Chapter 4. The red arrows show the power flows and blue arrows represent hydrogen flows.

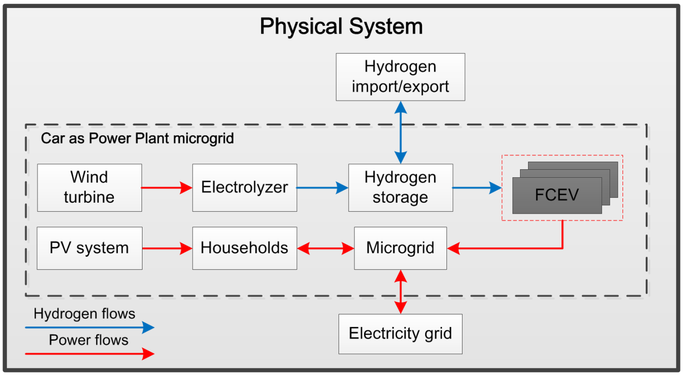


Figure 6.1: CaPP microgrid: Simplified description of the physical system operation

Rooftop solar photovoltaic (PV) panels are used to provide electricity to the households, and any surplus is exported. An external wind-to-hydrogen system is considered part of the microgrid system boundary. All the hydrogen produced is transported to the microgrid and stored in the storage and refilling system. Excess hydrogen in the system is exported, and when the storage level is low and hydrogen production insufficient, hydrogen is imported. To cover the residual demand, FCEVs are used to provide vehicle-to-grid. Following the fair scheduling mechanism in (Park Lee & Lukszo, 2016), the available FCEVs are switched on based on their cumulative number of start-ups. When modeling the technical system, the focus remains on the energy balance and the use of FCEVs to match the residual load and therefore the physical network and constraints are not considered in this model.

In the models of this thesis the physical system is simplified in a way that it includes the main conversion processes in a CaPP system. Moreover, aspects such as hydrogen production or storage outside the scope of the systems analyzed are not considered in detail. An example with a more detailed physical system description of a CaPP smart city can be found in Farahani et al. (2019), in which the hydrogen supply chain includes seasonal hydrogen storage in salt cavern.

6.2.2. Actor network

The physical components and flows explained above are controlled and influenced by the actors in the system. The **microgrid operator** makes decisions on the operation of the electrolyzer and takes care of hydrogen and power imports/exports. It also acts as the fuel cell car *aggregator*, and coordinates the vehicle-to-grid operations. As the entity governing the hydrogen system and vehicle-to-grid supply, it is also responsible of the related financial flows.

We consider the microgrid operator as the actor that takes the roles of operating the system and managing the transactions. However, different actors could take on the roles separately, depending on the organizational structure of the energy system.

Drivers are the actors that own and use the FCEVs on a daily basis. They make decisions on the driving, refilling and plug-in behavior. As vehicle owners, they also decide how to participate in vehicle-to-grid power supply. As mutually dependent actors, the microgrid operator and drivers need to have agreements regarding the V2G transactions.

The **households** are also considered, to determine the total load in the neighborhood and distribute the energy costs. Their behavior is not modeled in detail, and neither is their influence on the system operation.

Other actors that might be relevant in this system are actors with which the operator makes transactions to import/export hydrogen and power. Given the system scope, we do not model them endogenously.

6.2.3. Institutions

In this thesis, the institutional focus remains mostly on the vehicle-to-grid contracts and their role in the socio-technical system operation. However, we also make assumptions on the other relevant institutions.

Level 2: Regulation and policies

Policies are not considered explicitly in this research. However, we do assume some regulatory measures exist that allow vehicle-to-grid supply using FCEVs, as well as hydrogen conversion and storage in residential neighborhoods.

Level 3: Play of the game

Ownership The microgrid operator is the owner of the physical components of the microgrid system: including the PV panels, wind turbines, the electrolyzer and hydrogen storage and refilling system. It is also responsible for the V2G infrastructure, that is, the discharging poles installed in the neighborhood. As the owner, the aggregator is responsible for the investments. The drivers are considered to be the vehicle owners themselves. Households do not make other investments apart from the fuel cell vehicles.

Governance Outside of the microgrid, we assume the electricity system is operated similarly as today. The microgrid energy provider exchanges power by buying and selling electricity as a balance responsible party. We assume there is a hydrogen market in place, making it possible to exchange hydrogen. For the vehicle-to-grid supply, contracts between drivers and the microgrid operator are in place.

Vehicle-to-grid contracts As discussed in Chapter 5, bilateral contracts are the suitable type of governance for vehicle-to-grid supply. In this system, we consider volume-based contracts (VBC) and control-based contracts (CBC). With the first type, a certain amount of energy is committed to the microgrid operator, within a defined time interval. In the second case, there is no time or energy commitment. However, once the vehicle is plugged in, the operator is allowed to use the vehicle whenever needed. The only requirement for the microgrid operator is to respect the contractual guaranteed fuel level. In this case, the microgrid operator requests a minimum level of fuel for vehicles to plug-in, to prevent vehicles plugging in with very low energy levels. In both cases, the vehicle-to-grid remuneration consist of an energy and a capacity component. That way, vehicle owners can be paid for the amount of time they are plugged in and their vehicles are dispatchable.

In this chapter, we compare two different implementation strategies for each contract types. With the first type, we use **VBC-seasonal** and **VBC-flexible** contracts. This is to compare the seasonal requirements (high in winter, lower in summer) that may be defined by the microgrid operator against the more bottom-up, variable parameters defined by drivers. With the second type we use **CBC-seasonal** and **CBC-fixed** contracts. That is, the changing seasonal plug-in fuel requirements are compared to low fuel requirements.

Electricity supply contract As the sole energy provider in the microgrid, the microgrid operator also has a contract with households for the supply of electricity. Although not explicitly modeled as an object, the electricity supply contract defines the hourly price of electricity to be paid by households.

Level 4: Prices and quantities

Electricity prices The electricity price for the households in the neighborhood is set by the microgrid operator. It is defined as a real-time price, calculated based on the fraction of power delivered by each source: solar PV, FCEVs, and imports. The first is defined by the calculated levelized cost of electricity. The price of FCEV based power corresponds to the contractual vehicle-to-grid remuneration paid to drivers (both energy and capacity). Finally, for the import price from the grid, we assume a retail electricity price.

Hydrogen price The hydrogen price is set by the microgrid energy provider. The system levelized cost of hydrogen is calculated for the whole year. This value is used as the hydrogen price and is constant throughout the year.

V2G remuneration The remuneration for vehicle-to-grid is defined in the contracts. In both contract types, the price structure consists of an energy and a capacity payment. The vehicle owner is paid for the duration the car is plugged in and with enough fuel to be dispatched. When a vehicle is used to provide electricity to the microgrid, the owner also gets paid for the energy supplied. Both rates are constant throughout the year. The energy remuneration is defined as the cost of V2G electricity using fuel cell cars, plus a profit margin.

6.3. Agent-based model description

In this section, we describe the agent-based model, which was built in Python. The model is described following the ODD protocol (Grimm et al., 2006). After the *Overview* and *Design concepts* sections, we describe the elements of the *Details* in separate subsections and in a different order. More details of the ODD protocol can be found in Appendix A.

6.3.1. Overview

An agent-based model of the Car as Power Plant microgrid system described above is built. The physical system and its operation are modeled, as well as the actors and their actions. The contracts and other institutions are formalized as rules and conditions. To account for all transactions, prices are calculated as described previously.

Purpose

The modeling question addressed in this chapter is: *"How do volume-based and control-based contract parameters and contract implementation strategies influence the CaPP microgrid system operation and its actors?"*. To do this, we explore the implementation of volume-based and control-based contracts and their effects on the system's operational performance and its actors. We evaluate the performance from a physical and social system perspective, using three elements: the *reliability* criteria, the *economic* criteria, and the drivers' *autonomy* criteria. For the first category, we consider the system's self-supply capacity of hydrogen and electricity. In the second category, we consider the economic performance of all actors and the system. Finally, we look at how the V2G supply affects drivers' autonomy (freedom) in terms of plug-in hours and number of refilling occasions.

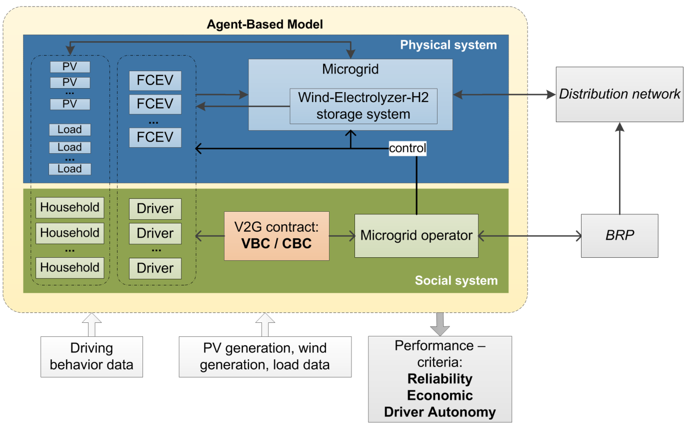


Figure 6.2: Agent-based model concepts: microgrid with fuel cell vehicles

Fig. 6.2 shows the model concepts and components corresponding to the physical and social systems. PV panels, which are owned by the microgrid operator, are placed in households to supply electricity. Plugged in FCEVs are used whenever PV generation is insufficient. If there is a shortage of vehicles, power is imported. A wind turbine is also used to produce hydrogen. Data sources are used to input driving schedules to the driver agents, the generation profile of PV panels and the wind turbine, and the electricity consumption in households. The evaluation of the system and agents' performance is based on the three categories mentioned above.

Agents and objects
The three types of agents and their objects are described in this section.

Driver agents This agent type represents both the characteristics of the driver and the vehicle's technical properties. The main variables are listed in Table 6.1. To define the conditions for V2G participation, each agent owns a **V2G contract object** (Table 6.2 and 6.3). For the complete list of driver agent variables, see Table A.1 in Appendix A.

V2G contract object Contracts between drivers and the microgrid operator define driver agents' participation and the conditions for using the vehicles for V2G. The contract parameters for the two contract types used in the model are shown in Table 6.2 and Table 6.3.

Household agents The households are modeled as simple agents that have no other behavior than to update the electricity consumption. In principle, driver agents are part of the household agents, but the relationship is not explored in this model. Their characteristics are listed in Table 6.4.

Microgrid operator agent The microgrid operator agent acts like an aggregator and uses the information to know which cars can be operated when needed. The microgrid operator owns and operates the microgrid's wind-electrolyzer-hydrogen storage system, as well as the PV systems. Table 6.5 shows the list of variables of the microgrid operator. For the complete list of the microgrid operator's variables, see Table A.2 in Appendix A. In addition, the microgrid operator's object variables are listed in Table A.3 in Appendix A.

Process overview
Figure 6.3 shows a flowchart with the main processes in the agent-based model. At the initialization, vehicle-to-grid contracts are created. Every hour, household agents consume electricity, which is either supplied by rooftop PV panels, by vehicles, or is imported. Driver agents either drive, refill or plug in their vehicle. The refilling and plug-in behavior is influenced by the contract parameters and in some cases by their refill strategy.

The microgrid operator checks the balance in the microgrid: if additional power is required, it operates available FCEVs. To do this, the microgrid operator takes into account the limits set by the contract parameters. Whenever the wind turbine is generating electricity, the electrolyzer is used to produce hydrogen, which is stored in the neighborhood. If the microgrid is not capable of supplying enough power, or when there is a surplus of PV generation, power is exchanged with the distribution grid. Hydrogen is also exchanged in case of surplus of shortage. The microgrid operator settles all the transactions at the end of each step. At the end of the evaluation period, the system

Table 6.1: Driver agent variables

Variable	Description	Data type
	Driver properties	
`arrival`	Arrival time at car park	Integer
`departure`	Departure time from car park	Integer
`distance`	Daily distance traveled	Integer
`drivingVariability`	Number of hours by which the arrival and departure times are changed (CBC)	Integer
`isAdjustContract`	State indicating whether the driver is changing its contract parameters (VBC)	Boolean
`isAdjustRefill`	State indicating whether the driver is changing its refill strategy (CBC)	Boolean
`minFuelDriving`	Daily fuel need for driving	Float
`fuelSF`	Safety factor to determine daily fuel need for driving	Float
`parkingDuration`	Number of hours the car is in the neighborhood	Float
`availableHours`	Total hours that the car could be used for vehicle-to-grid, removing the arrival hour and one hour for possible refilling	Float
`durFactor`	Fraction used to calculate the `duration` in VBC contracts	Float
`volFactor`	Fraction used to calculate the `maxVolume` in VBC contracts	Integer
`contract`	Vehicle-to-grid contract that specifies conditions for participation	Object
	Vehicle properties and states	
`dailyVolume`	Total daily volume of electricity supplied	Float
`fuelConsumption`	Fuel consumption when driving	Float
`fuelMax`	Maximum hydrogen capacity in vehicle's tank	Float
`hydrogenLevel`	Current level of hydrogen	Float
`usableFuel`	Maximum amount of fuel usable for V2G (`fuelMax` -`minFuelDriving`)	Float
`fuelAvailability`	Current fraction of fuel available for V2G (`hydrogenLevel`-`minFuelDriving`)	Float
`isDriving`	State indicating whether the driver is using the vehicle to drive	Boolean
`isHere`	State indicating whether the driver is in the parking garage	Boolean
`isRefilling`	State indicating whether the driver is using the vehicle to refill	Boolean
`isPluggedin`	State indicating whether the vehicle is plugged in	Boolean
`isV2G`	State indicating whether the vehicle is being used for V2G	Boolean
`Hrefill`	Amount of hydrogen refilled in current time step	Float
`pFCEV`	Amount of power being delivered using the vehicle in current time step	Float
`refillCondition`	Factor of available fuel to refill (CBC)	Float
`refillCount`	Total number of refilling instances	Integer
`startUps`	Total number of startUps	Float
`totalHrefill`	Total amount of hydrogen refilled throughout the simulation	Float
`totalPfcev`	Total power being delivered throughout the simulation	Float
	Techno-economic variables of vehicle use	
`V2GunitCost`	Cost of producing 1 kWh of electricity using the fuel cell	Float
`avgProfitV2Gdrivers`	Average profit of drivers during evaluation period	Float
`evalProfitV2G`	Total profit of V2G during evaluation period	Float
`totalProfitV2G`	Total profit from V2G at the end of simulation	Float
`totalRevenuesV2GC`	Total capacity revenues at the end of simulation	Float
`totalRevenuesV2GE`	Total V2G supply revenues at the end of simulation	Float
`totalRevenuesV2G`	Total revenues at the end of simulation	Float

Table 6.2: Volume-based vehicle-to-grid contract object variables

Variable	Description	Data type
`activation`	Daily time of the day at which V2G may be activated for the first time	Integer
`duration`	Number of hours a day that the vehicle is available while there is enough fuel	Integer
`maxVolume`	Maximum daily volume of electricity the aggregator is allowed to use from the vehicle	Integer
`minFuel`	Minimum fuel level that the vehicle needs before plug-in, so that `maxVolume` can be supplied and still leave enough fuel for driving	Float
`minFuelAvailability`	Minimum fraction of `usableFuel` that `minFuel` represents	Float
`V2Gprice`	Price paid to driver for every kWh supplied	Float
`capacityPrice`	Price paid to driver for every kW-h the vehicle is plugged in	Float

Table 6.3: Control-based vehicle-to-grid contract object variables

Variable	Description	Data type
`guarFuel`	Fuel level that the aggregator has to guarantee to driver after V2G	Float
`minFuel`	Minimum fuel level that the drivers need to plug-in	Float
`minFuelAvailability`	Minimum fraction of `usableFuel` that `minFuel` represents	Float
`V2Gprice`	Price paid to driver for every kWh supplied	Float
`capacityPrice`	Price paid to driver for every kW-h the vehicle is plugged in	Float

Table 6.4: Household agent variables

Variable	Description	Data type
`electricityConsumption`	Hourly electricity consumption	Float
`electricityCost`	Hourly cost of electricity	Float
`totalElectricityConsumption`	Total annual electricity consumption	Float
`totalElectricityCost`	Total annual cost of electricity	Float
`totalGrossEnergyCost`	Total annual cost of electric bill including electricity contract cost	Float

and agents' performance is calculated. Contract parameters can be adjusted after an evaluation period. At the end of the simulation, the same evaluation is carried out.

6.3.2. Design concepts

In this section we explain some of the design concepts of the agent-based model, following the ODD protocol (Grimm et al., 2006).

Emergence The main emergent properties of the model are the self supply % and the hourly electricity price. The first one depends on the residual load and the availability of the vehicles, together with the contract parameters. The latter depends on the amount of electricity that is supplied from each of the three possible sources: PV, fuel cell vehicles and imports. Moreover, the capacity price is added to this price, which depends on the vehicles plugged in at the time.

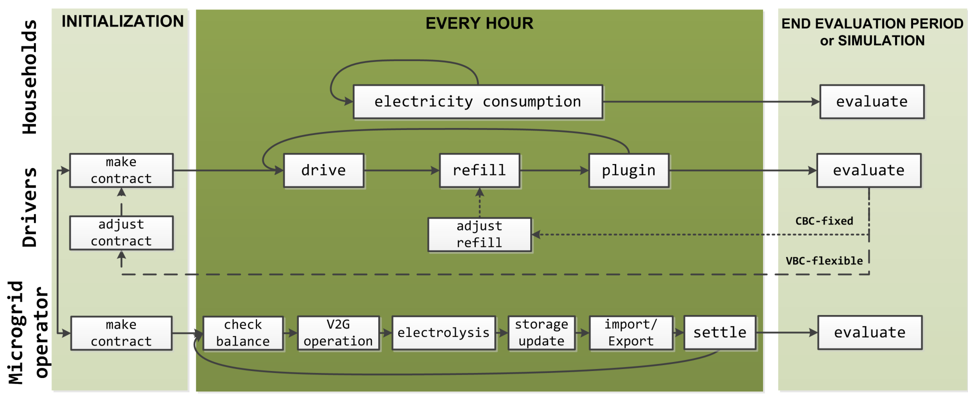


Figure 6.3: Flowchart CaPP microgrid

Table 6.5: Microgrid operator agent variables

Variable	Description	Data type
	Contracted drivers and households	
`drivers_list`	List of contracted drivers	Object (list)
`households_list`	List of contracted households	Object (list)
	System balance and V2G	
`aggregatedLoad`	Load from all households in current time step	Float
`aggregatedPV`	Aggregated PV generation	Float
`aggregatedV2G`	Aggregated V2G power in current time step	Float
`imbalance`	Imbalance of supply and demand in current time step	Float
`resLoad`	Residual load in current time step	Float
`requiredFCEVs`	Number of vehicles that are needed to serve the residual load	Integer
`dispatchedFCEVs`	Number of vehicles used for V2G	Integer
`pExport`	Power exported in current time step	Float
`pImport`	Power imported in current time step	Float
`PoP`	Preferred operating point of individual FCEVs	Integer
	Techno-economic variables and contract management	
`avgEvalProfit`	Average drivers' profit during evaluation period	Float
`isAdjustContract`	Status indicating changes in V2G contracts	Boolean
`elecContractCost`	Annual contract cost for electricity supply in households	Float
`elecPrice`	Electricity price in current time step	Float
`elecPriceImport`	Component of electricity price from electricity imports	Float
`elecPricePV`	Component of electricity price from PV generation	Float
`elecPriceV2G`	Component of electricity price from vehicle-to-grid	Float
`electricityCostsImport`	Cost of importing electricity in current time step	Float
`electricityCostsV2G`	Cost of V2G supply in current time step	Float
`electricityRevenuesHouseholds`	Revenues from households, in current time step	Float
`electricityRevenuesExport`	Revenues from electricity exports in current time step	Float
`hydrogenCostsImport`	Costs from hydrogen imports in current time step	Float
`hydrogenPrice`	Hydrogen price in the system	Float
`hydrogenRevenuesExport`	Revenues from hydrogen export in current time step	Float
`hydrogenRevenuesRefilling`	Revenues from hydrogen refilling in current time step	Float
`V2Gprice`	Price for 1 kWh of V2G supplied	Float
	PV system and Wind-Electrolyzer-Storage system	
`hSystem`	Hydrogen conversion and storage system	Object
`PVsystem`	PV system	Object
`windSystem`	Wind system	Object
	Total Costs and SLCoH, LCoE calculation	
`LCOE`	Levelized cost of PV electricity	Float
`SLCOH`	System levelized cost of hydrogen	Float
`TChydrogen`	Total annual costs of hydrogen	Float

Fitness Driver agents have profit as an implicit measure of their objective. Depending on the scenario, driver agents will adapt their behavior following this objective. In such cases, after each evaluation period, the driver compares its performance to other drivers in the microgrid. When an agent's economic performance is lower than the average, it will change its behavior to try to increase the net profit in the next period. For the microgrid operator, system reliability can be considered as the main measure objective. However, the microgrid operator does not change his behavior based on this measure.

Sensing At the evaluation step driver agents are informed of the average profit of all drivers that share the same parking profile. While there may be privacy concerns when sharing one's information, we assume that anonymity can be ensured.

Interaction Although driver agents do not interact directly with other driver agents, they are influenced by their performance. By comparing their own performance to the average, they make decisions on whether to change their refilling behavior. The microgrid operator interacts with drivers by providing information and by remunerating them based on their V2G service.

Prediction Drivers do not predict future conditions, but in some cases change their behavior to improve their economic performance. The microgrid operator does not predict future availability of vehicles or future prices.

Adaptation When drivers are modeled to be adaptive, they change their contract parameters to improve their profit from V2G. To do this, they either increase the time or the volume parameters in their vehicle-to-grid contract.

Stochasticity Initial states such as the hydrogen storage level or the drivers' hydrogen level are defined randomly between two bounds. Drivers' initial hydrogen level is also defined randomly. Moreover, different driving schedules are assigned every time using a probability distribution derived from data. In the CBC contract implementations, variability is also introduced in drivers so that their driving schedules vary every day in +- 1 hour.

Collectives The drivers that have a contract with the microgrid operator are represented by the `drivers_list`. The households are represented by the `households_list`.

Observation To observe the internal dynamics and system-level behavior, several outputs are gathered. At the system level, it is the balance of electricity and hydrogen, as well as the system electricity price. We also evaluate relevant outputs of every agent, such as the revenues, costs, or number of plug-in hours.

6.3.3. Submodels

In this section we describe the submodels of the agents, in relation to the flowchart in Fig. 6.3. We present the relevant equations, some of them using the variable names presented in Section 6.3.1. In other cases scientific notations are used to show how the different variables are calculated every time step. The list of the scientific notation is in the Nomenclature in Appendix B.4.

Drivers: `Make Contract` **- VBC**

Volume-based contracts can be fixed or dynamic. In this model we define two ways of implementing dynamic VB contracts: with *seasonal* parameters and *flexible* parameters.

Initially, the time duration and volume parameters are defined with two variables, `durFactor` and `volFactor`. For every driver, the parking duration is calculated. This is the number of hours the car is in the neighborhood and not driving, without considering the arrival hour. We assume that from the parked hours, the theoretical `availableHours` correspond to (`parkingDuration-2`). This is to ensure one hour is always free in case refilling is needed. Thus, the first activation hour is possible 2 hours after the scheduled arrival time. The contract parameters are calculated as indicated in equations 6.1 and 6.2.

$$\texttt{duration} = \texttt{round}(\texttt{durFactor} \cdot \texttt{availableHours}) \tag{6.1}$$

$$\texttt{maxVolume} = \texttt{min}(\texttt{duration} \cdot \texttt{PoP}, \texttt{volFactor} \cdot \texttt{PoP}) \tag{6.2}$$

Based on the maximum volume for V2G, the `minFuel` required at plug-in can be defined using equation

$$\texttt{minFuel} = \texttt{fuelSF} \cdot \texttt{minFuelDriving} + \frac{\texttt{maxVolume}}{\texttt{FCefficiency} \cdot \texttt{HHV}} \tag{6.3}$$

$$\texttt{minFuelDriving} = \texttt{fuelConsumption} \cdot \texttt{distance} \tag{6.4}$$

Seasonal parameters In the case of seasonal parameters, `durFactor` is initially 1. To calculate the volume for V2G, the `volFactor` is defined in Eq. 6.5. This factor depends on the `minFuelAvailability`, used by the microgrid operator to ensure all drivers provide the same percentage of `usableFuel`. The usable fuel is defined by the maximum fuel capacity in the tank and the guaranteed fuel level of each driver. The maximum volume `maxVol` is calculated as defined in equation 6.2.

$$\texttt{volFactor} = round(\texttt{usableFuel} \cdot \texttt{minFuelAvailability} \cdot \frac{\texttt{FCefficiency} \cdot \texttt{HHV}}{\texttt{PoP}}) \tag{6.5}$$

Fr example, in this chapter an initial `minFuelAvailability` of 0.5 is used to calculate the `volFactor` of all drivers. From June until the end of August, the parameters are reduced for all drivers by the microgrid operator. Both `durFactor` and `volFactor` are changed by a reduction factor and equations 6.1 and 6.1 are calculated again. When the summer period is over, the initial values are restored.

Flexible parameters In the flexible parameter scenario, volFactor is also calculated using equation 6.5. In this case, however, the minFuelAvailability is defined randomly between 0.25 and 0.50. The duration factor durFactor is defined randomly from 0.5 to 1. After every evaluation period, drivers can change their parameters to increase the commitment for V2G.

Drivers: Adjust Contract - VBC
In the flexible parameters scenario, drivers can update their contract parameters. They choose randomly whether to change the volume or duration factor.

$$\texttt{durFactor} = \texttt{durFactor} + \texttt{DUR\_CHANGE} \tag{6.6}$$

$$\texttt{volFactor} = \texttt{volFactor} + \texttt{VOL\_CHANGE} \tag{6.7}$$

Drivers: Make Contract - CBC
In the control-based contracts, the main parameters used are the guarFuel and minFuel. The guaranteed fuel level is defined based on the drivers' minimum fuel needs for driving, minFuelDriving (equations 6.8 and 6.4). The minimum fuel required at plug-in can also be fixed or dynamic. It is calculated using the minFuelAvailability and the drivers' usableFuel, as shown in eq. 6.9.

$$\texttt{guarFuel} = \texttt{fuelSF} \cdot \texttt{minFuelDriving} \tag{6.8}$$

$$\texttt{minFuel} = \texttt{guarFuel} + \texttt{minFuelAvailability} \cdot \texttt{usableFuel} \tag{6.9}$$

Seasonal and fixed parameters As Fig. 6.4 shows, the minimum fuel availability requirement indicates the minimum percentage of usable fuel that the vehicle must have when plugging in. This measure is used to apply the same requirements from all drivers, respecting their guaranteed fuel level. In the seasonal parameter implementation, the minimum fuel availability is initially defined as 0.5. In June it is changed to 0.35, and is restored to 0.5 at the end of August. On the other hand, in the fixed parameter implementation, a minFuelAvailability of 0.1 is used throughout the simulation. However, drivers change their refilling strategy to have more than the required minimum fuel available at plug-in.

Drivers: Adjust Refill - CBC
To define the refilling strategy in the fixed parameter implementation, we use the concept of **refill condition**. It represents the threshold of usableFuel that will trigger a driver to refill before plugging in the vehicle. Initially, it is equal to the minFuel requirement, so that a driver only refills to comply with the contract. However, drivers can increase the refillCondition in order to be triggered to refill more frequently and have higher fuel levels when plugging in.

$$\begin{aligned} \texttt{refillCondition} = round(&\texttt{refillCondition}+ \\ &\texttt{REFILL\_CHANGE} \cdot (\texttt{MAX\_REFILLCONDITION} - \texttt{refillCondition})) \end{aligned} \tag{6.10}$$

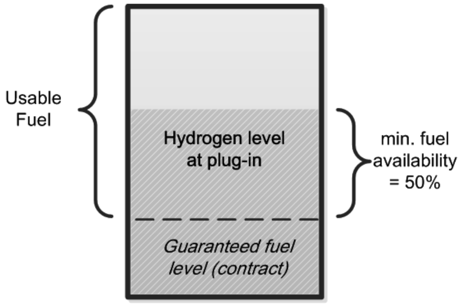


Figure 6.4: Concept of minimum fuel availability

Microgrid operator: `Check Balance`
The electricity balance is calculated as shown in equation 6.11:

$$P_t^{PV} - P_t^{load} + K_t = 0, \tag{6.11}$$

$$K_t = P_t^{V2G} + P_t^{imp} - P_t^{exp} \tag{6.12}$$

where the aggregated power from fuel cell vehicles $P_t^{V2G} = \sum_{i=1}^{N} P_{it}^{fcev}$ is primarily used for the residual load, i.e. when $K_t > 0$. Whenever it is insufficient, power is imported P_t^{imp}. Thus,

$$if \begin{cases} K_t > 0 & P_t^{V2G} + P_t^{imp} > 0,\ P_t^{exp} = 0 \quad (6.13a) \\ K_t < 0 & P_t^{V2G} = 0,\ P_t^{imp} = 0,\ P_t^{exp} > 0 \quad (6.13b) \\ K_t = 0 & P_t^{V2G} = 0,\ P_t^{exp} = 0,\ P_t^{imp} = 0 \quad (6.13c) \end{cases}$$

Microgrid operator: `V2G operation`
For choosing which vehicles to use, the fair scheduling mechanism from Section 4.2.3, that is, based on the start-up count of the available vehicles. The calculation of start-up and shut-down of vehicles is explained Section 4.2.3

Microgrid operator: `Electrolysis`
The amount of hydrogen produced in the electrolyzer is calculated as:

$$H_t^{prod} = P_t^{el} \cdot \Delta t \cdot \frac{\eta_{el}}{HHV} \tag{6.14}$$

where $P_t^{el} = P_t^{wind}$.

Microgrid operator: `Storage update`
The hydrogen balance is shown in equation 6.15:

$$HS_t = HS_{t-1} + H_t^{prod} + H_t^{imp} - H_t^{ref} - H_t^{exp} \tag{6.15}$$

Microgrid operator: `Settle`

The hourly price for the electricity in the microgrid has two components: the energy price and the capacity price (eq. 6.16).

$$p_t^{el} = p_t^{en} + p_t^{cap} \tag{6.16}$$

The hourly electricity price in the microgrid depends on the supply of power from the different sources, as shown in 6.17.

$$p_t^{en} = \frac{P_t^{PV}}{P_t^{load}} \cdot p_{PV} + \frac{P_t^{V2G}}{P_t^{load}} \cdot p_{V2G} + \frac{P_t^{imp}}{P_t^{load}} \cdot p_{imp} \tag{6.17}$$

Moreover, households pay for the V2G capacity available every hour.

$$p_t^{cap} = \frac{\sum_{i=1}^{N_{fcevs}} p_{V2GC} \cdot PoP \cdot z_{it}}{N_{households}} \tag{6.18}$$

Where z_{it} indicates the plug-in status of vehicle i at time t.

The price of PV, p_{PV}, is defined by the annual levelized cost of electricity from PV (LCoE). The equations of the total costs of each component can be found in Appendix A.

$$LCoE = \frac{TC_{PV}}{\sum_{t=0}^{8760} P_t^{PV} \cdot \Delta t} \tag{6.19}$$

The price of V2G electricity p_{V2G} is defined with the following equation:

$$p_{V2G} = c_{V2G} \cdot (1 + m_{V2G}) \tag{6.20}$$

Where c_{V2G}, the unit cost of producing electricity through V2G is defined as:

$$c_{V2G} = \frac{p_{H2}}{HHV \cdot \eta_{FC}} + \frac{CC_{FC}}{LT_{FC}} \cdot 0.5 \tag{6.21}$$

The price of hydrogen p_{H2} is defined by the annual levelized cost of hydrogen (LCoH), which is calculated using the total amount of hydrogen produced in the year and the total annual cost of hydrogen. The latter includes the costs of the following components: 1) wind turbine, 2) electrolyzer, 3) reverse osmosis, 4) rainwater collector, 4) hydrogen storage, 5) hydrogen compressor, and 6) hydrogen dispenser. The cost of transporting hydrogen to the microgrid are not included. The equations for the LCoH are found in Appendix A.

Finally, the imported electricity is bought also at a constant rate p_{imp} and corresponds to the retail electricity price.

All agents: `Evaluate`

The total profit from hydrogen for the **microgrid operator** is calculated as:

$$profit_j^{HS} = \sum_{t=0}^{T} (r_{jt}^{HS} + r_{jt}^{Hexp} - c_{jt}^{Himp}) - TC_{hydrogen} \tag{6.22}$$

where the total costs of hydrogen $TC_{hydrogen}$ are defined as:

$$TC_{hydrogen} = TC_{el} + TC_{wind} + TC_{HS} + TC_c + TC_d + TC_{rw} + TC_{ro} \tag{6.23}$$

that is, as a function of the total costs of the electrolyzer, wind turbine, hydrogen storage, compressor, hydrogen dispenser, rainwater collector and reverse osmosis. The equations of the total costs of each component can be found in Appendix A.

For the microgrid operator, the total annual profit from electricity sales is defined as:

$$profit_j^e = \sum_{t=0}^{T} (r_{jt}^e + r_{jt}^{e,exp} - c_{jt}^{e,imp}) - TC_{PV} - TC_{dis} \tag{6.24}$$

$$r_{jt}^e = \sum_{h=1}^{H} c_h^e = \sum_{t=0}^{T}\sum_{h=1}^{H} p_t^e \cdot P_{ht}^{load} \tag{6.25}$$

The total costs for every **driver** *i* over a period T consist of the cost of V2G supply and the refilling costs.

$$c_i = \sum_{t=0}^{T} (c_{it}^{V2G} + c_{it}^{ref}) \tag{6.26}$$

$$c_{it}^{V2G} = P_{it}^{fcev} \cdot \Delta t \cdot c_{V2G} \tag{6.27}$$

The refilling costs for drivers are:

$$c_{it}^{ref} = p_{H2} \cdot H_{it}^{ref} \cdot y_{it} \tag{6.28}$$

The revenues for the driver over a period T are those corresponding to the vehicle-to-grid energy and capacity remuneration.

$$r_i = \sum_{t=0}^{T} r_{it}^{V2GE} + r_{it}^{V2GC} \tag{6.29}$$

$$\text{where: } r_{it}^{V2GE} = p_{V2G} \cdot P_{it}^{fcev} \tag{6.30}$$

$$r_{it}^{V2GC} = p_{V2GC} \cdot PoP \cdot z_{it} \tag{6.31}$$

Thus, the annual profit for a driver is defined as:

$$profit_i^{V2G} = r_i^{V2GE} + r_i^{V2GC} - c_i^{V2G} \tag{6.32}$$

$$c_i^{ref} = \sum_{t=0}^{T} p_t^{H2} \cdot H_{it}^{ref} \tag{6.33}$$

The total gross annual energy cost for the **households** corresponds to the annual electricity cost c_h^e plus the contract cost $c_h^{contract}$, which covers the annual V2G discharger cost TC_{V2Gd}, as indicated in equations 6.34 and 6.35.

$$c_h^{e,gross} = c_h^e + c_h^{contract} \tag{6.34}$$

$$c_h^{contract} = \frac{TC_{V2Gd}}{N_{Households}} \tag{6.35}$$

Table 6.6: Techno-economic input parameters. Source: (Oldenbroek et al., 2017)

Variable	Value
HHV	39.41 kWh/kg
Electrolyzer efficiency (η_{el})	82%
FCEV efficiency (η_{FC})	61%
FCEV fuel consumption	0.006024 kg hydrogen/km
Water input	8.92 kg water/kg hydrogen

Table 6.7: Technical component properties and costs. Source: (Oldenbroek et al., 2017)

Component	Capital Costs	Lifetime (years)	O&M Costs, %
Electrolyzer	250 €/kg	30	3.20
Compressor	4,200 €/kg/h	10	2
Hydrogen Storage	575 €/kg	30	1
Dispenser	72,890 €/unit	10	1.1
Rainwater collector	21,030 €/m^3/day	50	0.33
Reverse Osmosis	1.2 €/L/day	25	4.8
PV system	440 €/kWp	30	4.7
Wind turbine	800 €/kW	30	3.2
Discharger poles	3,200 €/4-unit	15	5
FCEV	21.7 €/kW	8,000 hours	5

6.3.4. Input parameters and data

The input data used for the driver behavior, hourly weather and load data are the same as in 4.3.1. The techno-economic input parameters and costs are shown in Table 6.6. Table6.7 and Table 6.8 are used to calculate the total costs of the system.

6.3.5. Model assumptions

The underlying assumptions of this model are listed in Table 6.9:

6.3.6. Performance evaluation

The purpose of using fuel cell vehicles for vehicle-to-grid in this microgrid is to provide electricity to households when there is a shortage of PV generation. This service is managed and remunerated by the microgrid operator, who passes the cost on to the

Table 6.8: Technical component capacity or units

Component	Capacity or units
Electrolyzer	335 kW
Compressor	1
Hydrogen Storage	430 kg
Dispenser	1 units
Rainwater collector	1 units
Reverse Osmosis	1 units
PV system (aggregated)	500 kW (17m^2 per rooftop)
Discharger poles	13 units

Table 6.9: Model assumptions

	Model assumptions
1	Driving and refilling of FCEVs occur within one hour time steps.
2	Driving schedules are constant, except for two scenarios.
3	The generation of electricity from each household's PV system is the same.
4	The electricity demand from each household is the same.
5	Hydrogen produced in the wind-to-hydrogen system is transported directly to the neighborhood's central hydrogen storage without losses and is readily available.
6	Electricity consumption for water purification, compression and storage of hydrogen are not included in this model.
7	The preferred operating point of FCEVs as power plants is 10kW[1].
8	Hydrogen and power can be imported and exported.
9	Whenever possible, the frequent switching on-off of FCEVs is avoided by operating FCEVs that are already switched on.
10	The price of hydrogen in the microgrid is constant throughout the year.
11	The price of hydrogen imports/exports is the same as the price in the microgrid.
12	The remuneration for V2G energy and capacity is constant throughout the simulation.
13	The driving schedules are set up to represent parking profiles in a residential neighborhood. Thus, from the two daily trips, *departure from* the neighborhood occurs before arrival *to the neighborhood*.
14	The minimum parking duration is of 3 hours, including the arrival time, an hour for possible refilling, and one minimum hour for vehicle-to-grid.

households. The conditions for V2G including the remuneration are specified by the V2G contracts. To evaluate how a V2G contract implementation affects the system performance, we observe the performance from a *physical* and *social* perspective. Therefore, the reliability, economic, and autonomy criteria are considered to observe trade-offs in the performance indicators (Lo Prete et al., 2012). The criteria and indicators are listed in Table 6.10.

Reliability criteria From a physical system perspective, the performance can be measured in terms of self-supply of electricity (R1) and hydrogen (R2). While the main goal of vehicle-to-grid is to increase the self-sufficiency of electricity supply in the microgrid, the self-supply of hydrogen is also affected. Increased vehicle-to-grid implies higher hydrogen consumption.

Economic criteria From a social system perspective, the economic performance of all involved actors can be measured. The hourly electricity price in the microgrid is calculated based on the amounts and prices of renewable energy supply, V2G supply, V2G capacity, and power imports. Thus, different mean prices can be expected with different V2G contracts. This leads to different average electricity prices (E1).

All the costs of electricity supply are passed on to the households, and therefore

Table 6.10: Performance criteria and indicators

Criteria	Indicator	Name	Units	Attribute of
Reliability	R1	Electricity self-supply	%	System
	R2	Hydrogen self-supply	%	System
Economic	E1	Mean electricity price	cents/kWh	System
	E2	Profit from hydrogen	€/year	Microgrid operator agent
	E3	Electricity costs	€/year	Household agents
	E4	Profit from V2G	€/year	Driver agents
	E5	No. of start-ups	times/year	Driver agents
Autonomy	A1	Plug-in hours	hours/year	Driver agents
	A2	Refill count	times/year	Driver agents

the microgrid operator's profits from electricity only depend on the price of PV used and the total annual costs. This does not change based on the contracts used. The microgrid operator's profit from hydrogen, however, may change under different V2G contracts (E2). This is because of the variation in hydrogen consumption and self-supply percentage. Household agents pay for the electricity supplied. Since the mean electricity price is affected by the V2G contract used, their costs will also change (E3). For the drivers, the V2G contract implemented has two implications. Firstly, the mean profit levels from V2G will change due to the difference in volumes and plug-in hours (E4). An implicit additional cost is represented by the number of start-ups (E5). Fuel cell operation, especially the start-up/shut-down processes lead to fuel cell degradation and eventual replacement costs.

Drivers' autonomy criteria Another performance criteria is the drivers' autonomy level. As mentioned above, participation in V2G inevitably leads to some loss of autonomy. Firstly, this can be seen in the amount of plug-in hours (A1). These hours can be considered as hours that drivers would not able to use the vehicle for additional trips. The supply of V2G also leads to higher number of refill instances (A2). This might be due to the actual volume used, but is also influenced by the minimum fuel requirements `minFuel` for plugging in. While the higher refilling costs can be compensated by increased revenues from V2G, additional trips to the refilling station can be considered to be a burden. If drivers have to refill almost every day before plugging in, the perception will be that freedom and comfort are lost to some extent.

6.3.7. Model verification

To confirm whether the model and sub-models were implemented correctly, we carried out the verification - following the steps indicated in (K. H. Van Dam et al., 2013). An overview of the tests carried out is shown in Table 6.11. In the Appendix A we explain the tests 2 through 4 in more detail, with the corresponding figures and tables.

The first test, recording and tracking behavior, was carried out at an earlier stage by using the `print` function. This allowed the observation of the agents' internal processes. Also, before the final simulation experiment a variability testing was done by carrying out

50 repetitions.

Table 6.11: Overview of verification tests

	Test	Description
1	Recording and tracking behavior	`print` function to communicate changes in agent states.
2	Single-agent testing	1 Microgrid operator, 1 Driver agent. Driver methods: `makeContract`, `drive`, `refill`, `plugin`, `adjustSeasonalContract`.
3	Interaction testing in a minimal model	1 Microgrid operator, 1 Household, 2 Driver agents. Microgrid operator methods: `V2Goperation`, `settle`, `evaluate`. Driver methods:`adjustRefill`, `adjustContract`.
4	Multi-agent testing	1 Microgrid operator, 200 Households, 50 Drivers: all previous methods.
5	Variability testing	50 repetitions carried out.

As indicated in Table 6.11 the single-agent testing was done with one microgrid operator and one driver agent to test the driver methods. The minimal model was built with another driver agent and with one household agent. This allowed the verification of additional methods, such as the V2G operation, settling of V2G remuneration and evaluation of drivers' performance. Finally, the multi-agent testing was initialized with the same inputs as the base case simulation, and the same methods were tested. Extreme value testing was also carried out to break the agents, in the single-agent and minimal model testing. After some corrections following the single-agent testing, the expected outcomes were obtained and therefore the model is considered to be verified.

6.3.8. Model validation

Following the model verification the model validation is carried out to evaluate whether the model built is appropriate for addressing the modeling question. According to K. H. Van Dam et al. (2013), there are several methods to validate a model: through historic replay, expert consultation - also known as face validation, literature validation and model replication. When a model is built to explore mechanisms and phenomena that cannot yet be observed in the real world, expert validation becomes a useful approach to validate the model. As the model presented in this chapter explores the implementation of vehicle-to-grid contracts with fuel cell vehicles and new prosumer behavior of drivers, it is not possible to validate the results using historical or empirical data.

The model assumptions and mechanisms, as well as the results, were presented to an expert in the field. The three criteria used to evaluate the system performance were also considered appropriate for the analysis. Moreover, at different stages of the model development, the concepts were presented in publications, discussed with peers and refined accordingly. Therefore, the model is deemed appropriate to answer the research question of this chapter.

6.4. Simulation and results

In this section we present the results of the simulation experiments. First, we introduce the initialization of the four scenarios that were run for 8760 steps corresponding to one year, with fifty repetitions. Then, we present the results of the multi-criteria analysis, where the performance is evaluated using the reliability, economic, and driver autonomy criteria. The sensitivity runs are carried out to test the agents' adaptive behavior, the capacity payments, and other external aspects, including the criteria used in the analysis. Finally, the findings of this chapter are discussed at the end, followed by concluding remarks.

6.4.1. Initialization

To compare V2G contract types and implementations we define the scenarios presented in Table 6.12.

Table 6.12: Simulation experiments

	Scenario	**Implementation**	**Defined by**	**Adaptive behavior drivers**
1	VBC-seasonal	Seasonal `maxVol`, `duration`	MG operator	None
2	VBC-flexible	Flexible `maxVol`, `duration`	Driver	Adjust contract
3	CBC-seasonal	Seasonal `minFuel`	MG operator	None
4	CBC-fixed	Fixed `minFuel`	MG operator	Adjust refill strategy

Table 6.13: Model initialization

Variable	**Value**	**Scenario**
`numMGoperators`	1	All
`numDrivers`	50	All
`numHouseholds`	200	All
`ticks`	8,760	All
`V2GprofitMargin`	0.05	All
`LCOE` (PV)	0.05286 euro/kWh	All
`elecPricePV`	0.056 euro/kWh	All
`elecPriceImport`,`elecPriceExport`	0.20 euro/kWh	All
`SLCOH`	2.1844 euro/kg	All
`hydrogenPrice`	2.29 €/kg	All
`V2GcapacityPrice`	0.01 €/kW-h	All
`reductionDuration`	0.7	VBC-seasonal
`reductionVolume`	0.7	VBC-seasonal
`DUR_CHANGE`	0.1	VBC-flexible
`MAX_DURATIONFACTOR`	1	VBC-flexible
`VOL_CHANGE`	0.1	VBC-flexible
`MAX_VOLUMEFACTOR`	0.9	VBC-flexible
`reductionMinFuel`	0.7	CBC-seasonal
`REFILL_CHANGE`	0.15	CBC-flexible
`MAX_REFILLCONDITION`	0.9	CBC-flexible

The inputs in Table 6.13 are used in each scenario. The prices of PV electricity and hydrogen are calculated with a 5% profit margin from the levelized cost of electricity (PV) and system levelized cost of hydrogen. In each simulation, we created 50 driver agents that were initialized with the mobility data from (Centraal Bureau voor de Statistiek

(CBS) & Rijkswaterstaat (RWS), 2015) as explained in Section 4.3.1. The initial hydrogen level in their tanks is set as a random value, from 3.0 to 5.64 kg.

Table 6.14: Initialization of volume-based contracts

Variable	VBC-seasonal	VBC-flexible	Equations
activation	arrival + 2	arrival + 2	
duration	durFactor = 1	durFactor = [0.5 to 1]	eq. 6.1
maxVolume	minFuelAvailability=0.5	minFuelAvailability=[0.25 to 0.5]	eq. 6.2, 6.5
minFuel	f(minFuelDriving, maxVolume)	f(minFuelDriving, maxVolume)	eq. 6.3
V2Gprice	V2GUnitCost*(1 + V2GprofitMargin)	V2GUnitCost*(1 + V2GprofitMargin)	eq.6.20
capacityPrice	0.01 €/kW-h	0.01 €/kW-h	
evalPeriod	None	30 days	

For the scenarios VBC-seasonal and VBC-flexible, we initialized contracts according to Table 6.14 and as explained in Section 6.3.3. For the CBC-seasonal and CBC-fixed scenarios, we initialize contracts indicated in Table 6.15 and as explained in Section 6.3.3. In the CBC-fixed scenarios, an initial `refillCondition` of 0.1 is used.

Table 6.15: Initialization of control-based contracts

Variable	CBC-seasonal	CBC-fixed	Equations
guarFuel	fuelSF*minFuelDriving	fuelSF*minFuelDriving	eq. 6.8
minFuel	minFuelAvailability = 0.5	minFuelAvailability = 0.1	eq. 6.9
V2Gprice	V2GUnitCost*(1 + V2GprofitMargin)	V2GUnitCost*(1 + V2GprofitMargin)	eq.6.20
capacityPrice	0.01 €/kW-h	0.01 €/kW-h	
evalPeriod	None	30 days	

6.4.2. Energy balance

The annual electricity balance is shown in Table 6.16. From the solar electricity generated, roughly half of it is used directly in the households and the rest is exported. Approximately 68% of the load has to be covered by FCEVs or imports. Table 6.17 shows the amount of residual load supplied from vehicle-to-grid and the electricity imports. In the CBC-seasonal and CBC-fixed scenarios, most of the residual load is covered by V2G. In the VBC scenarios, the seasonal contracts show a higher average amount of V2G supplied, with lower variability than with the flexible contract implementation.

Table 6.16: Electricity balance

Load	PV	Residual Load	PV to Load	Excess PV	Units
680.01	407.94	465.76	214.26	193.69	MWh

All the wind energy generated is used to produce hydrogen in the electrolyzer, as shown in Table 6.18. In total, around 28 tons of hydrogen are produced in a year. Due to the limited storage capacity in the microgrid's, hydrogen is also exchanged. Table 6.19 shows the average amount of hydrogen refilled, imported and exported in all scenarios.

Table 6.17: Residual Load supply, in MWh

		V2G supplied		Imported	
Scenario	**Residual Load**	Mean	s.d.	Mean	s.d.
VBC-seasonal	465.76	460.1	5.2	5.6	5.2
VBC-flexible		448.1	8.8	17.7	8.8
CBC-seasonal		463.2	2.4	2.5	2.4
CBC-fixed		461.8	4.7	4.0	4.7

Table 6.18: Hydrogen production

Wind, MWh	Hydrogen produced, tons
1,339.5	27.9

The results show that higher V2G supply is followed by higher local consumption of hydrogen. As a result, more hydrogen needs to be imported. The microgrid system is a net exporter of both electricity and hydrogen.

6.4.3. Multi-criteria analysis

The amount of V2G supplied is influenced by the type of contract implemented. As explained in Section 6.3.6 three types criteria are used to evaluate the overall performance. Table 6.20 shows the main results in the reliability, economic, and autonomy criteria. The mean values and standard deviation of the performance indicators in every scenario run are listed.

To determine the comparative performance across scenarios, we normalize the results as shown in Table 6.21. Indicators in the reliability criteria are normalized using a minimum value of 0 and maximum value of 100. Indicators E1 to E5 are normalized using the lowest (or worst) results as the minimum value and highest (or best) results as the maximum values. For A1, a lower bound of 8760 and higher bound of 0 are used. Similarly, for A2 a lower bound of 365 and higher bound of 0 are used. The average within each category is calculated to compare the overall performance in the three criteria.

Table 6.19: Hydrogen balance, in tons

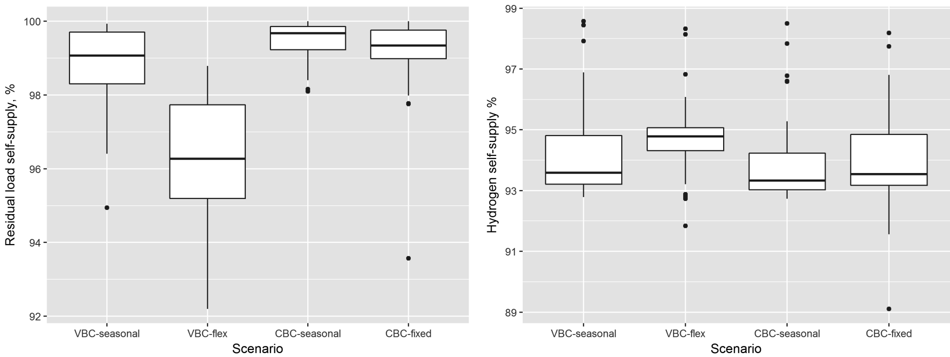
		Refilled		Imported		Exported	
Scenario	**Produced**	Mean	s.d.	Mean	s.d.	Mean	s.d.
VBC-seasonal	27.9	24.3	0.6	1.4	0.3	5.0	0.4
VBC-flexible		23.9	0.6	1.3	0.3	5.2	0.5
CBC-seasonal		24.5	0.5	1.5	0.3	4.9	0.4
CBC-fixed		24.4	0.7	1.4	0.4	4.9	0.4

Table 6.20: Results: Mean and standard deviation of each performance indicator

			VBC-seasonal		VBC-flexible		CBC-seasonal		CBC-fixed		
Criteria	**Indicator**	**Attribute of**	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	Units
Reliability	R1: Self-supply electricity	System	98.79	1.12	96.20	1.90	99.46	0.52	99.15	1.00	%
	R2: Self-supply hydrogen	System	94.19	1.41	94.65	1.17	93.87	1.35	94.04	1.54	%
Economic	E1: Mean elec. Price	System	9.72	2.47	9.76	2.55	10.08	2.49	10.04	2.47	cent/kWh
	E2: Profit: Hydrogen	Microgrid operator agent	2,965.33	142.62	2,931.41	148.94	2,980.04	163.53	2,973.88	140.32	€/year
	E3: Costs: Electricity	Household agents	421.40	4.55	419.09	5.62	454.29	4.51	450.40	5.07	€/year
	E4: Profit: V2G	Driver agents	422.72	23.09	388.56	29.29	560.73	21.04	542.19	24.51	€/year
	E5: Start-ups	Driver agents	214.39	5.01	213.26	5.42	168.78	5.62	180.36	4.86	times/year
Autonomy	A1: Plug-in hours	Driver agents	3,782.62	227.71	3,452.69	287.58	5,159.79	208.86	4,975.72	242.48	hours/year
	A2: Refill count	Driver agents	138.60	3.94	125.47	5.32	113.92	2.60	107.76	3.61	times/year

Table 6.21: Comparative performance of each indicator across scenarios

Indicator	**VBC-seasonal**	**VBC-flexible**	**CBC-seasonal**	**CBC-fixed**
R1: Self-supply electricity	0.99	0.96	0.99	0.99
R2: Self-supply hydrogen	0.94	0.95	0.94	0.94
Reliability performance	**0.965**	**0.954**	**0.967**	**0.966**
E1: Mean elec. Price	1.00	0.87	0.00	0.10
E2: Profit: Hydrogen	0.70	0.00	1.00	0.87
E3: Costs: Electricity	0.93	1.00	0.00	0.11
E4: Profit: V2G	0.20	0.00	1.00	0.89
E5: Start-ups	0.00	0.02	1.00	0.75
Economic performance	**0.566**	**0.379**	**0.600**	**0.545**
A1: Plug-in hours	0.57	0.61	0.41	0.43
A2: Refill count	0.62	0.66	0.69	0.70
Autonomy performance	**0.594**	**0.631**	**0.549**	**0.568**



(a) Residual load self-supply (b) Hydrogen self-supply

Figure 6.5: Self-supply percentage in the microgrid

Reliability criteria

In terms of reliability, control-based contracts perform better than volume-based contracts. The VBC-flexible scenario has the lowest performance. The self-supply percentage is an aggregate system-level result that is influenced by all actors and the environment. The reliability performance has two implications, indicating: 1) the extent to which the microgrid can ensure the energy supplied has been generated from renewable sources, and 2) a reduced dependence on the national grid for energy supply. The percentage of residual load covered by vehicle-to-grid in each scenario is shown in Figure 6.5a. In general, control-based contract scenarios have a higher self-supply percentage. This is because of the higher plug-in times and energy available in the vehicles. In the volume-based contract scenarios, there is a big difference between the seasonal and flexible contracts. Despite the fact that after every evaluation period, flexible contracts allow the adjustment (increase) of parameters, flexible contracts have lower volumes and plug-in durations in general.

The comparative performance in hydrogen self-supply follows almost an opposite order. The amount of hydrogen imported increases when there is more V2G in the microgrid. Therefore, the CBC scenarios have the lowest self-supply percentages. The VBC-flexible scenario has the highest self-supply percentage. In this model, the import/export costs of hydrogen are considered to be the same as the price of hydrogen in the microgrid. However, prices outside the microgrid may differ. In that case, hydrogen imports could influence the hydrogen prices in the microgrid, and eventually the V2G profitability.

Economic criteria

The economic performance is highest also in the CBC-seasonal scenario, but it is closely followed by the CBC-fixed and VBC-seasonal scenario. The VBC-flexible is the contract implementation that leads to lowest economic performance.

Microgrid operator The best scenario for the microgrid operator in terms of profit is the CBC-seasonal scenario, due to the profit from hydrogen, which depends on the

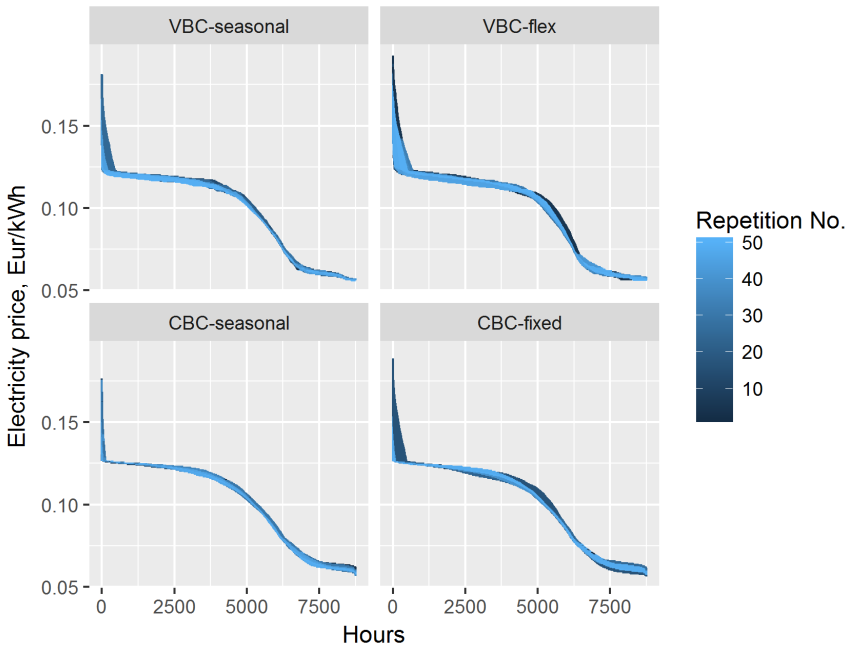
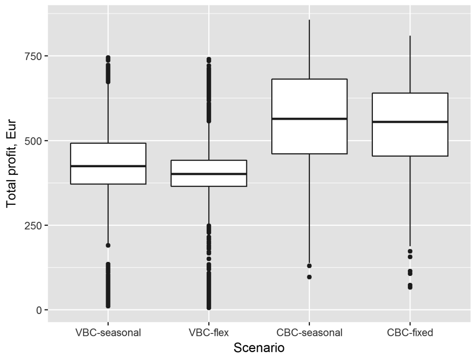


Figure 6.6: Price duration curve in four scenarios

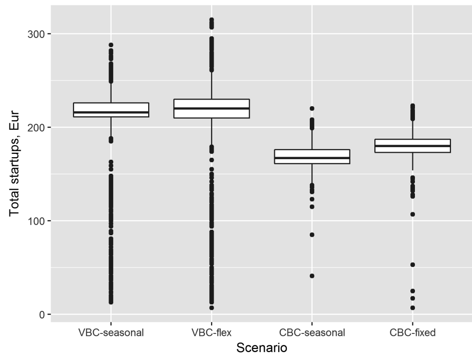
hydrogen sold. In this scenario, both the amount of hydrogen refilled and exported are relatively high (Table 6.19).

System At the system level, the hourly electricity prices resulting from the supply of V2G energy, V2G capacity, and the imports are different for each scenario. As Table 6.20 indicates, the average electricity price is between 9.72 (VBC-seasonal) and 10.08 (CBC-seasonal) euro cent/kWh. The hourly electricity prices resulting in each scenario run and repetition are sorted in descending order in Fig. 6.6. The VBC scenarios show higher peak prices than the CBC scenarios due to the higher amount of power imported. However, the average prices are lower with VBC contracts because of the lower capacity payments.

Households Overall, lower energy costs can be seen in the VBC scenarios. The electricity bill paid by households at the end of the year consists of the sum of hourly electricity costs plus the yearly contract fee. This fee covers the annual V2G discharger costs. Although households' energy costs have a very close relationship to the electricity prices, the comparative performance is slightly different, as shown in Table 6.21. While the lowest average electricity price is in the VBC-seasonal scenario, the lowest annual costs correspond to the VBC-flexible scenario.



(a) Drivers' annual profits from V2G



(b) Number of start-ups at the end of the year

Figure 6.7: Drivers' economic implications

Drivers Average annual profits for drivers range from 388.56 (VBC-flexible) to 560.73 €/year (CBC-seasonal). The profitability of V2G is related to drivers' availability in terms of plug-in time, and this is related to the fuel levels as well. For each contract type, the extent to which drivers participate is higher in the more 'strict' implementations (seasonal). So are their profits, as shown in Fig. 6.7a. The average number of start-ups are shown in Fig.6.7b. They are lowest in the CBC-seasonal scenario, with 168.8 times/year (3.2 times/week), and highest in the VBC-seasonal scenario, with 214.4 times/year (4.1 times/week). Comparing the two contract types, we observe that a higher number of plugged in vehicles imply fewer start-ups on average for all drivers. The CBC-seasonal scenario has the lowest number of start-ups due to the high plug-in hours and higher fuel availability required in the contract.

Autonomy criteria

Finally, the driver autonomy performance is highest in the VBC scenarios, as expected. The participation of drivers in V2G means that drivers lose the freedom to use the vehicle for additional trips. It also means that drivers have to refill more frequently because of the fuel used for V2G. Overall, the VBC-flexible scenario has the highest autonomy performance. This is due to the low plug-in duration and volumes committed.

In terms of plug-in hours, both CBC scenarios are highest and thus the autonomy is lowest. This is because of the assumption that drivers plug in the vehicle whenever they are in the neighborhood. Although there is no actual commitment of plugging in, vehicles are plugged in for more hours. With the CBC contracts scenario, the average total plug-in hours are lower in the CBC-fixed scenario because there is a lower fuel requirement. Vehicles may plug-in with very low amounts of hydrogen. Once they are used, they might reach the guaranteed fuel level sooner, making the car unavailable for V2G. Although drivers adjust their refill strategy, the plug-in hours are still lower than in the seasonal contract implementation.

The VBC scenarios have higher refill counts than the CBC scenarios. The commitment of volume means that drivers always have to make sure there is enough fuel before plugging in. This may lead to more frequent refilling before plugging in. The count is higher in the seasonal scenario because of the higher volumes committed. In the control-based contracts, the seasonal implementation has a higher refill count due to the high requirement of fuel before plugging in. This has similar implications as the volume-based contracts.

6.4.4. Sensitivity analysis

The system's overall performance depends on the actors' behavior but also the decisions made regarding the contracts. Moreover, this performance is influenced eventually by the way in which the results are analyzed in the multi-criteria assessment. Following the base case simulation of the four scenarios, we perform a sensitivity analysis to test some assumptions used in the simulations and the multi-criteria assessment.

First, we remove the adaptive behavior in the drivers to observe the change when drivers do not react to their performance evaluation. This is to see how much the assumption on the adaptive behavior of drivers influences the results. Then, we test various assumptions that may influence the economic performance. First, we remove the capacity payments used in the vehicle-to-grid supply contracts. These payments increase the economic performance of drivers, especially in the CBC scenarios. Then, we test several increasing levels of hydrogen price in the microgrid. Higher prices increase the cost of V2G, and therefore we expect the electricity prices to go up. Next, we analyze the effect of the retail electricity price used as the rate for exchanging electricity with the grid. We reduce this price to see to what extent it can decrease electricity prices in the microgrid. Finally, we change the structure multi-criteria assessment. The criteria categories are changed in order to compare drivers' performance to the rest (system and other actors). While the number of drivers is only a fraction of the number of households, they are the prosumers that provide the back-up electricity when renewable generation is not available. Therefore, a different way to assess the performance can be used to inform drivers in their decision-making process.

S1: Removing adaptive behavior

In the scenarios VBC-flexible and CBC-fixed, drivers evaluate their performance every month. Based on their performance they either adjust contract parameters (VBC) or the refilling strategy (CBC). These strategies are aimed at increasing participation, both explicitly (hours, volume committed) or implicitly (increasing level of fuel availability). This represents their intuitive way to increase participation and profit from V2G and is based on the assumption that participation is driven by a willingness to maximize profit, but that decision-making abilities of drivers are limited (bounded rationality). However, it does not take into account the behavior of drivers that do not want to change under any circumstances. In the first sensitivity analysis, we remove the adaptive behavior and run the two simulations for 8760 hours with 50 repetitions.

Table 6.22 shows the results of these two runs. Table A.27 in Appendix A shows the change in the average values of the S1 results with respect to the base case simulation. While there is not much difference in the reliability and system-level performance, the economic and autonomy performance of drivers is affected negatively.

The normalized values are calculated in Table 6.23 with the base case simulations for the seasonal runs. Without the adaptive behavior, the only change in ranking in

Table 6.22: S1 Results: Mean and standard deviation of each performance indicator

	VBC-flexible (S1)		CBC-fixed (S1)		
Indicator	mean	s.d.	mean	s.d.	Units
R1: Self-supply electricity	94.38	2.01	99.33	0.81	%
R2: Self-supply hydrogen	95.07	0.89	93.63	1.15	%
E1: Mean elec. Price	9.71	2.61	10.00	2.44	cent/kWh
E2: Profit: Hydrogen	2,906.74	154.94	2,959.63	148.25	€/year
E3: Costs: Electricity	409.55	3.65	447.46	3.66	€/year
E4: Profit: V2G	332.80	17.29	532.16	18.91	€/year
E5: Start-ups	238.06	4.97	185.92	4.74	times/year
A1: Plug-in hours	2,903.34	166.92	4,874.59	186.60	hours/year
A2: Refill count	109.99	3.99	92.39	2.04	times/year

the comparative performance is the economic criteria. In this case, the VBC-seasonal scenario performs best out of the four, instead of the CBC-seasonal scenario.

Table 6.23: S1: Comparative performance of each indicator across scenarios

Indicator	VBC-seasonal	VBC-flexible (S1)	CBC-minfuel	CBC-free (S1)
R1: Self-supply electricity	0.99	0.94	0.99	0.99
R2: Self-supply hydrogen	0.94	0.95	0.94	0.94
Reliability performance	**0.965**	**0.947**	**0.967**	**0.965**
E1: Mean elec. Price	0.97	1.00	0.00	0.20
E2: Profit: Hydrogen	0.80	0.00	1.00	0.72
E3: Costs: Electricity	0.74	1.00	0.00	0.15
E4: Profit: V2G	0.39	0.00	1.00	0.87
E5: Start-ups	0.34	0.00	1.00	0.75
Economic performance	**0.649**	**0.400**	**0.600**	**0.541**
A1: Plug-in hours	0.57	0.67	0.41	0.44
A2: Refill count	0.62	0.70	0.69	0.75
Autonomy performance	**0.594**	**0.684**	**0.549**	**0.595**

S2: No capacity payments

In the following analysis we remove the capacity payment and increase the V2G profit margin for drivers from 5% to 10%. The capacity payments are used in this chapter and with these contracts as a way to reward the availability (CBC) of vehicles and to remunerate their commitment (VBC). In systems where vehicle-to-grid is used for reliability purposes, we expect that a commitment will be needed from participating vehicles. In the simulation experiments, a capacity payment of 0.01 €/kW-h was used. Moreover, the energy remuneration was calculated with a 5% profit margin over the cost of vehicle-to-grid. Therefore, the structure is changed to see the effect of the capacity payments on the economic performance of the system and the actors. We run the four scenarios for 8760 hours with 50 repetitions. Table 6.24 shows the results of the economic performance indicators, followed by Table 6.25 with the normalized values. Table A.28

in Appendix A shows the change percentage between the average of the S2 simulations and the base case.

Table 6.24: S2 Results: Mean and standard deviation of economic performance indicators

	VBC-seasonal (S2)		**VBC-flexible (S2)**		**CBC-seasonal (S2)**		**CBC-fixed (S2)**		
Indicator	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	Units
E1	8.94	2.20	9.04	2.32	8.92	2.18	8.91	2.17	cent/kWh
E2	2,949.95	136.69	2,923.24	137.84	2,957.30	131.34	2,948.10	161.62	€/year
E3	337.34	1.82	342.00	4.28	336.47	1.34	336.27	1.14	€/year
E4	89.16	0.75	87.24	1.77	89.52	0.55	89.60	0.47	€/year
E5	215.55	4.28	218.35	5.43	168.07	4.76	176.31	4.73	times/year

Table 6.25: S2: Comparative performance of each indicator across scenarios

Indicator	**VBC-seasonal (S2)**	**VBC-flexible (S2)**	**CBC-seasonal (S2)**	**CBC-fixed (S2)**
R1: Self-supply electricity	0.99	0.97	0.99	1.00
R2: Self-supply hydrogen	0.94	0.94	0.94	0.94
Reliability performance	**0.965**	**0.956**	**0.969**	**0.967**
E1: Mean elec. Price	0.80	0.00	0.96	1.00
E2: Profit: Hydrogen	0.78	0.00	1.00	0.73
E3: Costs: Electricity	0.81	0.00	0.97	1.00
E4: Profit: V2G	0.81	0.00	0.97	1.00
E5: Start-ups	0.06	0.00	1.00	0.84
Economic performance	**0.654**	**0.000**	**0.979**	**0.913**
A1: Plug-in hours	0.57	0.61	0.41	0.42
A2: Refill count	0.62	0.65	0.69	0.70
Autonomy performance	**0.593**	**0.632**	**0.552**	**0.557**

When removing the capacity payments, the profit potential for drivers depends only on the amount of V2G supplied. Thus, profits are highest in the CBC-seasonal scenario, where the self-supply of electricity is also highest. Removing capacity payments also influences the average electricity prices (by -8 to -11%) and the electricity bill for households (by -18 to -25%). The highest influence, however, is on the drivers' average profits from vehicle-to-grid (indicator E4), which sees a sharp decrease by -78 to -84% across the four scenarios. Although a reduced energy bill can be beneficial for households, a suitable remuneration structure should be found to benefit both households and drivers.

In all the criteria, the ranking of highest and lowest performing contract implementations stays the same. However, the VBC-flexible scenario notably performs lowest in all the economic indicators, leading to a score of 0.

S3: Hydrogen prices

In this analysis we test increasing hydrogen prices in the microgrid. In the base case simulations, the hydrogen price is 2.29 €/kg, based on the annual SLCoH of 2.18 €/kg, taking into account a small profit margin for the microgrid operator. Given that this hydrogen price is not taxed and that there could be normalized hydrogen prices in the

Table 6.26: S3: Comparative performance of economic indicators across scenarios

Indicator	VBC-seasonal (S3)	VBC-flexible (S3)	CBC-seasonal (S3)	CBC-fixed (S3)
S3.1 Hydrogen price 2.50 €/kg				
E1: Mean elec. Price	1.00	0.81	0.00	0.10
E2: Profit: Hydrogen	0.17	0.00	1.00	0.84
E3: Costs: Electricity	0.99	1.00	0.00	0.09
E4: Profit: V2G	0.16	0.00	1.00	0.93
E5: Start-ups	0.00	0.06	1.00	0.76
Econ. performance	**0.465**	**0.373**	**0.600**	**0.544**
S3.2 Hydrogen price 2.75 €/kg				
E1: Mean elec. Price	1.00	0.87	0.00	0.09
E2: Profit: Hydrogen	1.00	0.21	0.00	0.51
E3: Costs: Electricity	0.96	1.00	0.00	0.10
E4: Profit: V2G	0.16	0.00	1.00	0.91
E5: Start-ups	0.00	0.08	1.00	0.74
Econ. performance	**0.625**	**0.432**	**0.400**	**0.471**
S3.3 Hydrogen price 3.00 €/kg				
E1: Mean elec. Price	0.98	1.00	0.00	0.11
E2: Profit: Hydrogen	0.00	0.14	0.59	1.00
E3: Costs: Electricity	0.86	1.00	0.00	0.10
E4: Profit: V2G	0.22	0.00	1.00	0.91
E5: Start-ups	0.00	0.03	1.00	0.72
Econ. performance	**0.413**	**0.435**	**0.518**	**0.569**

future, we explore the effect of increasing hydrogen prices on the economic performance of the system. This represents an imposed hydrogen price, and the total costs of hydrogen production or the SLCoH do not change. Therefore, the hydrogen profit calculation for the microgrid operator will have the same total costs as in the base case simulation. From a base case value of 2.29 €/kg we increase the price of hydrogen to 2.50 €/kg (S3.1), 2.75 €/kg (S3.2) and 3.00 €/kg (S3.3). We run the four scenarios for 8760 hours with 50 repetitions.

Table 6.27 shows the mean and standard deviation of the economic indicators, followed by Table 6.30, which shows the normalized values. The change percentage between S3 and the base case are shown in Table A.29 in Appendix A. The most notable changes are in the annual profit from hydrogen. This is because the total costs of hydrogen production in the system were kept the same while increasing the price of hydrogen for consumers.

Increasing the hydrogen price by 9% increases the average electricity price by 6% in all contract implementations. In S3.2, a hydrogen price increase of 20% rises the average electricity price by 13% in all contract implementations. In S3.3, an increase of 31% in the hydrogen price rises the average electricity price by about 20% in all contract implementations. Figure 6.8 shows the effect of increasing hydrogen price on the price-duration curve of the microgrid. The increase in total electricity costs for households caused by the rise in hydrogen price is 1 to 3% lower than the rise in mean electricity

Table 6.27: S3 Results: Mean and standard deviation of economic indicators

	VBC-seasonal (S3)		**VBC-flexible (S3)**		**CBC-seasonal (S3)**		**CBC-fixed (S3)**		
Indicator	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	Units
S3.1 Hydrogen price 2.50 €/kg									
E1: Mean elec. Price	10.30	2.83	10.37	2.93	10.68	2.87	10.64	2.82	cents/kWh
E2: Profit: Hydrogen	8,794.33	176.01	8,789.25	151.14	8,819.08	154.72	8,814.21	149.43	€/year
E3: Costs: Electricity	441.41	4.86	441.13	5.55	476.34	3.86	473.17	4.78	€/year
E4: Profit: V2G	423.67	23.39	395.09	27.07	568.39	19.36	556.36	22.24	€/year
E5: Start-ups	214.30	4.46	211.76	4.62	168.04	4.32	179.04	4.22	times/year
S3.2 Hydrogen price 2.75 €/kg									
E1: Mean elec. Price	11.01	3.31	11.06	3.36	11.38	3.31	11.35	3.29	cents/kWh
E2: Profit: Hydrogen	15,812.63	158.18	15,768.49	170.30	15,756.84	193.97	15,785.37	173.90	€/year
E3: Costs: Electricity	466.47	4.61	465.21	5.45	500.80	4.74	497.40	3.90	€/year
E4: Profit: V2G	426.57	19.99	398.96	26.39	570.43	21.05	555.30	18.92	€/year
E5: Start-ups	214.90	4.24	211.18	4.44	167.13	5.23	179.51	4.41	times/year
S3.3 Hydrogen price 3.00 €/kg									
E1: Mean elec. Price	11.74	3.76	11.73	3.78	12.09	3.78	12.05	3.75	cents/kWh
E2: Profit: Hydrogen	22,707.53	199.70	22,722.94	201.81	22,771.05	167.26	22,815.11	170.48	€/year
E3: Costs: Electricity	493.43	4.70	488.30	4.48	525.79	5.16	521.97	3.94	€/year
E4: Profit: V2G	439.15	20.69	400.41	22.53	573.33	23.05	557.18	18.52	€/year
E5: Start-ups	214.38	5.84	213.00	4.23	167.85	5.41	180.82	4.84	times/year

prices. The profit for drivers also increases, by a smaller percentage. This is due to the 5% of profit that is used to calculate the energy remuneration for V2G. Since this is calculated over the cost of V2G, a higher hydrogen price leads to higher remuneration for drivers and net revenues.

S4: Retail electricity price

In this analysis we change the retail electricity price used in the simulation. In the previous simulations, the electricity price used for exchanging electricity between the microgrid and the grid was assumed to be 0.20 €/kWh, thus, similar to current retail prices. While electricity prices could decrease in the future due to higher penetration of renewable sources, the cost of increasing the flexibility of the system could keep the retail prices at current levels. Due to this uncertainty of this assumption, we explore the effect of a lower exchange price of 10 cents/kWh on the economic performance of the system, which would be at a similar level to the V2G energy remuneration. Again, we run the four scenarios for 8760 hours with 50 repetitions.

Table 6.28: S4 Results: Mean and standard deviation of economic indicators

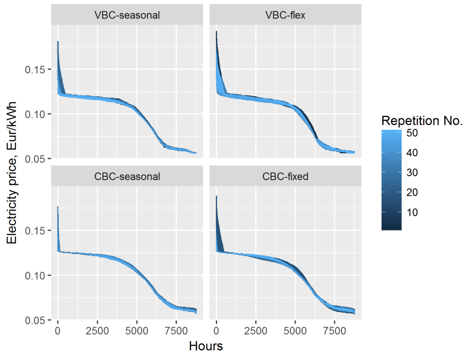
	VBC-seasonal (S4)		**VBC-flexible (S4)**		**CBC-seasonal (S4)**		**CBC-fixed (S4)**		
Indicator	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	Units
E1	9.65	2.43	9.55	2.43	10.05	2.47	10.02	2.44	cents/kWh
E2	2,988.74	131.26	2,949.02	161.22	2,943.87	121.06	2,959.59	143.65	€/year
E3	418.53	4.70	409.90	5.48	453.11	6.44	450.24	5.88	€/year
E4	422.52	18.99	387.06	22.26	561.01	25.98	549.53	23.69	€/year
E5	214.47	3.49	212.73	4.07	167.89	4.83	178.97	5.05	times/year

In Table 6.28 we show the results of the economic indicators, followed by Table 6.29 with the normalized results for the economic indicators. Table A.30 in Appendix A shows the change percentage of the results with respect the base case simulation.

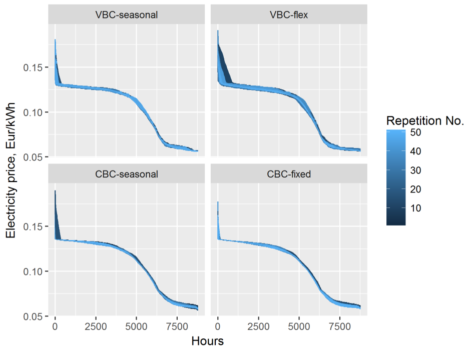
Table 6.29: S4: Comparative performance of economic indicator across scenarios

Indicator	**VBC-seasonal (S4)**	**VBC-flexible (S4)**	**CBC-seasonal (S4)**	**CBC-fixed (S4)**
E1: Mean elec. Price	0.80	1.00	0.00	0.07
E2: Profit: Hydrogen	1.00	0.11	0.00	0.35
E3: Costs: Electricity	0.80	1.00	0.00	0.07
E4: Profit: V2G	0.20	0.00	1.00	0.93
E5: Start-ups	0.00	0.04	1.00	0.76
Econ. performance	**0.560**	**0.430**	**0.400**	**0.436**

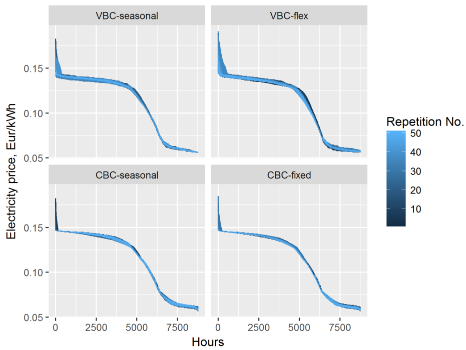
A reduction of the retail electricity price by 50% leads to a decrease in average electricity prices, albeit by only -0.22 to -2.15%. The annual electricity bill for households is also reduced by a similar percentage. Changes in the average hydrogen profit for the microgrid operator and V2G profits for drivers are less than +-2%. The results show that with a lower exchange electricity price, the VBC-seasonal contract implementation leads to highest economic performance. In conclusion, the effect of a lower retail electricity price does not lead to significant changes in the electricity prices and households' electricity bill, but changes the comparative economic performance across scenarios.



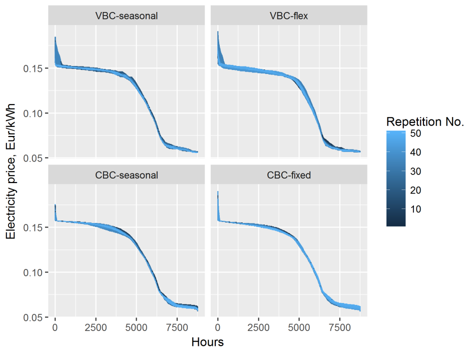
(a) Base case Hydrogen price 2.29 €/kg



(b) S3.1 Hydrogen price 2.50 €/kg



(c) S3.32 Hydrogen price 2.75 €/kg



(d) S3.3 Hydrogen price 3.00 €/kg

Figure 6.8: S3: Total price-duration curve

S5: Drivers' performance Vs. rest

In the final analysis, we change the structure of the multi-criteria assessment. The initial evaluation uses performance indicators classified into reliability, economic and driver autonomy criteria. In this classification, the performances of the system and actors are mixed within the criteria. Many of the indicators correspond to the drivers, as fuel cell cars are a central part in the residual energy supply of the microgrid. Therefore, we use the same indicators to classify the performance criteria into 'drivers' performance' and the rest ('system and other actors'). That is, we consider the profits from V2G (E4), the number of start-ups (E5), the plug-in hours (A1) and refill count (A2) in one category. Table 6.30 show the average performances for drivers and the rest of the system, using the normalized results from the base case simulation (Table 6.21).

The drivers' performance alone is highest in the CBC-seasonal scenario, with the highest profit levels (1.0) and lowest start-ups (1.0). Although plug-in hours are highest (thus, worst), the number of refill count is the second lowest (0.689) across the four scenarios. For the rest of the system, the VBC-seasonal scenario is by far the best performing contract implementation. It has high reliability as well as low electricity costs and fair profit levels for the microgrid operator.

Table 6.30: S5: Normalized results: performance score across scenarios

Indicator	VBC-seasonal	VBC-flexible	CBC-seasonal	CBC-fixed
R1: Self-supply electricity	0.99	0.96	0.99	0.99
R2: Self-supply hydrogen	0.94	0.95	0.94	0.94
E1: Mean elec. Price	1.00	0.87	0.00	0.10
E2: Profit: Hydrogen	0.70	0.00	1.00	0.87
E3: Costs: Electricity	0.93	1.00	0.00	0.11
System and other actors	**0.912**	**0.755**	**0.587**	**0.604**
E4: Profit: V2G	0.20	0.00	1.00	0.89
E5: Start-ups	0.00	0.02	1.00	0.75
A1: Plug-in hours	0.57	0.61	0.41	0.43
A2: Refill count	0.62	0.66	0.69	0.70
Drivers' performance	**0.347**	**0.322**	**0.775**	**0.694**

6.4.5. Overview

Table 6.31 shows the highest and lowest performing contract implementations in the base case and sensitivity simulations. In the reliability and economic performance, the VBC-flexible contract consistently performs badly. Except for the S1 simulations, the CBC-seasonal scenarios performs best. In terms of autonomy, the VBC-flexible scenario performs best and CBC-seasonal performs worst in all simulation runs.

However, when considering drivers' performance as a whole, the autonomy performance is overshadowed by the economic performance. As a result, the best implementation is the CBC-seasonal scenario, while the VBC-flexible scenario leads to lowest performance. For the rest of the system, the CBC-seasonal becomes the lowest performing implementation while the VBC-seasonal performs best.

Therefore, the results show that with the three criteria defined at the beginning,

Table 6.31: Overall comparative performance across scenarios in each simulation run (highest vs. lowest)

	Reliability criteria		Economic criteria		Autonomy criteria	
Simulation	*High*	*Low*	*High*	*Low*	*High*	*Low*
Base case	CBC-seasonal	VBC-flex	CBC-seasonal	VBC-flex	VBC-flex	CBC-seasonal
S1	CBC-seasonal	VBC-flex	VBC-seasonal	VBC-flex	VBC-flex	CBC-seasonal
S2	CBC-seasonal	VBC-flex	CBC-seasonal	VBC-flex	VBC-flex	CBC-seasonal
S3.1	CBC-seasonal	VBC-flex	CBC-seasonal	VBC-flex	VBC-flex	CBC-seasonal
S3.2	CBC-seasonal	VBC-flex	VBC-seasonal	CBC-seasonal	VBC-flex	CBC-seasonal
S3.3	CBC-seasonal	VBC-flex	CBC-fixed	VBC-seasonal	VBC-flex	CBC-seasonal
S4	CBC-seasonal	VBC-flex	VBC-seasonal	CBC-seasonal	VBC-flex	CBC-seasonal
	System & other actors		**Drivers**			
	High	*Low*	*High*	*Low*		
S5	VBC-seasonal	CBC-seasonal	CBC-seasonal	VBC-flex		

the 'stricter' CBC-seasonal contract implementation is best for the reliability (and economic) aspects, at the expense of drivers' autonomy. On the other hand, the more 'relaxed' VBC-flex implementation requires a reduced loss of autonomy but usually leads to the lowest economic and reliability performances.

In the sensitivity analysis, we tested a few assumptions and input parameters. The first was the drivers' adaptive behavior and the rest were economic assumptions and inputs used. In each case, the comparative reliability and autonomy performance remains the same, and only the ranking in economic performance changes. This shows that the use of contracts can provide a robust way to ensure a certain level of reliability in the system, and that the expected loss of autonomy can be determined to inform the actors. However, the price of hydrogen, the remuneration structure and the exchange electricity prices will determine the type of contract implementation that is most economically attractive.

The economic criteria in the assessment, however, includes performance indicators that relate to the system, to the 200 households and the 50 drivers. Since there is a big dependence on fuel cell vehicles, the drivers' criteria were compared to the rest of the system. When considering the drivers performance separately, the drivers' results are more in line with the reliability and economic performances (CBC-seasonal best/VBC-flex worst) and the autonomy aspects do not seem to have a big influence. For the rest of the system, however, the CBC-seasonal implementation has the lowest score due to the high average electricity price and high electricity costs for households.

6.5. Discussion

The different scenarios explored in this chapter show that contract types and implementations have different effects on the system and the involved agents. With the multi-criteria analysis we analyzed the system performance from a socio-technical system perspective, taking into account reliability, economic and autonomy criteria. The approach used to analyze the effect of contracts and the multi-criteria assessment can be used as a basis for decision-making for the development of such a microgrid. In this section, we further discuss some insights and limitations from this chapter.

Vehicle-to-grid remuneration

The purpose of this model is not to find the optimal energy and capacity prices for V2G. However, the results show that different contract types lead to different plug-in hours and supplied volumes (or potential), and therefore the effect of both energy and capacity payments should be used when determining the remuneration structure.

The results also show that the net revenues for drivers mostly consist of the capacity payments. These costs are covered by the households, and it can be seen as the cost of reliability in the system. While we assumed that the existence and/or level of the capacity payments do not influence drivers' behavior, it seems to be an important aspect to consider when trying to engage drivers in vehicle-to-grid. It is possible that without capacity payments drivers would not be interested. Capacity payments can play a big role as they 1) provide a *fixed* income to drivers for their participation, as opposed to the variable energy remuneration 2) reward drivers for their availability (CBC), or remunerate drivers for their commitment (VBC), and therefore 3) can be used to attract potential participants.

While taxes are not considered in V2G remuneration or energy prices in the microgrid, they will be an important element to explore when considering policy options to support the development of hydrogen and the implementation of vehicle-to-grid.

Trade-offs

The results confirm that there is a trade-off to be made between reliability & overall economic aspects and the autonomy loss of drivers. Based on the multi-criteria assessment, CBC-seasonal contracts may be chosen because of the high reliability and economic performance, but drivers have to be willing to lose some autonomy in the way they use their cars. On the other hand, VBC-flexible contracts reduce the extent to which drivers are engaged in V2G but lead to lower reliability and economic performance. This changes, however, when the multi-criteria assessment compares the performance of drivers (economic and autonomy) to the performance of the rest of the system. The increased revenues seem to outweigh the loss of autonomy in the analysis.

Decision-making

In our multi-criteria assessment we assume that all indicators have the same weight. If it is demonstrated that one of the indicators is more important than others, the results would change. To implement this in practice, a survey would be needed to determine which of the indicators is more relevant to the involved actors. We also explored the performance of drivers with the rest of the system, due to the dependence on vehicle-to-grid for reliability purposes. However, given that there are more households than drivers, and that drivers actually belong to a household each, households' opinions may be more valuable. In each project, the decision-making would be heavily influenced by the social dynamics of the involved actors. Together, they should find a way to analyze the system performance and make decisions based on how the indicators are grouped and weighed.

Physical system assumptions
There are some assumptions used in the physical system that also have an effect on the system performance. Firstly, the hydrogen produced in the wind-to-hydrogen system is transported directly to the microgrid. Since the wind turbine is not in the neighborhood, in a real system there would be a delay in the state of hydrogen storage. Also, the consumption of electricity in the equipment, especially compression and hydrogen storage were not included. While not so significant, these increase the electricity consumption in the system, and therefore the V2G demand and costs for households. One important aspects in the operation of the electrolyzer is the availability of water. Although this is assumed not to be a problem, it could limit the production of hydrogen at times of drought.

Assumptions in driving behavior
In the experiments, the driving schedules are constant throughout the simulation. Only in the control-based contracts we introduce variability in -1 to +1 hour to reflect possible changes in arrival and departure times. However, additional trips during the day are not taken into account. In a real system, this would have a bigger influence on the autonomy of drivers. With volume-based contracts, there would be no possibility to use the vehicle during plug-in hours, whereas control-based contracts would be more flexible. If a car is plugged in but not in V2G mode, the driver could use the car for driving and plug-in again at a later time. As a result, plug-in hours may be reduced more flexibly, leading to reduced loss of autonomy. On the other hand, a volume commitment can also help drivers have a perception of reduced uncertainty.

In a system with variable driving times and additional trips, the availability of cars for V2G would be reduced. The effect would probably be stronger with volume-based contracts – especially the flexible implementation. With control-based contracts, the reduction in vehicle availability would depend on the actual time needed for additional trips. The model can be further improved by adding more variability and stochasticity in driver behavior.

6.6. Conclusions

In this chapter, we explored the effect of volume-based and control-based contracts on the performance of a CaPP microgrid, using an agent-based model. We used two different implementations for each contract to reflect two types of strategies. First, one in which parameters are fixed by the microgrid operator seasonally (high in winter, low in summer). Second, one in which requirements are low or defined freely by drivers, but in which drivers slowly try to increase their participation after evaluating their contract on a monthly basis.

The performance of the system is defined using indicators corresponding to three categories: reliability, economic and driver autonomy criteria. These represent the effect that different V2G contracts may have on the physical and social systems. The results show that while there is a consistent winner in reliability and economic criteria (CBC-seasonal) for this given system, there is a trade-off to be made with the loss of drivers' autonomy. Thus, while the VBC-flexible scenario is best for drivers' autonomy, it leads to the lowest economic and reliability performances.

Testing different economic inputs and assumptions, we observed that the comparative performance of the reliability and autonomy criteria remain unchanged. In some cases, however, they do affect the ranked performance of the economic indicators. Increasing hydrogen prices influence the average electricity price in the microgrid and the households' electricity bill, although the effect is limited. A reduced retail electricity price does not reduce costs significantly, but it does so more notably in the VBC-flexible scenario, where there are more imports from the grid.

The model presented in this chapter can be used to conclude how different contract implementations influence the operation of a microgrid system. Moreover, the relevant indicators can be grouped into different criteria, as it was done in the latest sensitivity test. When grouping all indicators relevant to drivers (economic and autonomy), the results seem to be more in line with the general reliability and economic performance. Therefore, if drivers give the same importance to their economic and autonomy indicators, the most appropriate contract type for the given system could be the CBC-seasonal implementation.

The system explored in this chapter represents a very concrete example of a CaPP microgrid setting and organizational and ownership structure. Changes in assumptions on the aspects external to the microgrid or the ownership structure of the system would lead to different outcomes. To evaluate what type of contract implementation is most suitable for a certain system, the interests of the actors involved in the design process could be incorporated in quantitative terms. If those interests and needs are known, the conceptualization of the performance evaluation presented in this chapter could be used to perform a multi-criteria assessment by assigning appropriate weights to each category. Thus, the results will ultimately depend on who is involved in the process, and what criteria are the most relevant.

7

CaPP in the electricity market: Price-based contracts

7.1. Introduction

In this chapter we also address the last research sub-question: *"How do different contract types and rules affect the operation of vehicle-to-grid in CaPP systems?"*. As such, the high level purpose is similar to Chapter 6, that is, to formalize V2G contracts in an agent-based model and explore their effects on the operation of a system. In this case, however, we investigate a different type of CaPP system, namely a Car-Park Power Plant (CPPP), where aggregated FCEVs supply electricity in the wholesale electricity market through an aggregator. This is another type of CaPP system that represents a different type of V2G supply. In a CaPP microgrid, the role of FCEVs is to supply electricity reliably when local renewable generation is insufficient. In the case of the CPPP we explore the profit potential of FCEVs in wholesale electricity markets.

Since this type of CaPP system implies that drivers are exposed to varying electricity prices, we turn to a different type of V2G contract: price-based contracts. This contract types can be used to ensure that a FCEV is used only when electricity prices are above the amount desired by the driver.

We envision the CPPP system embedded in future electricity systems with higher renewable energy penetration. Therefore, we compare the role of price-based contracts in energy scenarios with different electricity price levels. Moreover, we also investigate the effect of two dispatch rules used by the aggregator, which could have a big impact on the remuneration structure and thus the performance of all actors. While in Chapter 6 we only used a dispatch rule based on the number of accumulated start-ups in each vehicle, we introduce a dispatch rule based on fuel availability.

The goal of the CPPP agent-based model presented in this chapter is to understand how price-based V2G contract parameters and the aggregator's dispatch strategies affect the system performance, under different energy scenarios. To evaluate the performance of involved actors, we focus on annual net profit. Given the heterogeneity of the driver agents, we analyze the common characteristics of driver with certain level of profit at the end of a year.

The chapter is structured as follows: first, we introduce the CPPP as a socio-technical system. We describe the physical system, the main actors and the institutions in place. Then, we describe how the concepts are used to formalize and build an agent-based model. We present the results of the simulation runs and provide a discussion of the results.

7.2. System description

7.2.1. Physical system

The Car Park Power Plant is a car park that is equipped with discharger poles for connecting FCEVs to the grid. It also consists of on-site renewable generation, an electrolyzer and a hydrogen storage and refilling system. Thus, it can be considered a Virtual Power Plant with storage. As Fig. 7.1 shows, the physical operation of the CPPP involves hydrogen and power flows. The electrolyzer is used to convert water into hydrogen, using electricity from the solar PV system or the grid. This hydrogen is then compressed and stored in the car park. Fuel cell vehicles refill their tanks at the hydrogen storage and refilling system. When plugged in, the fuel cell stack in the cars can be operated to supply vehicle-to-grid power. At times of shortage, hydrogen is imported via a pipeline into the car park, and when it is produced in excess, it is exported. The amount of hydrogen refilled by drivers in the system depends both on the daily driving needs and the amount of hydrogen used for vehicle-to-grid.

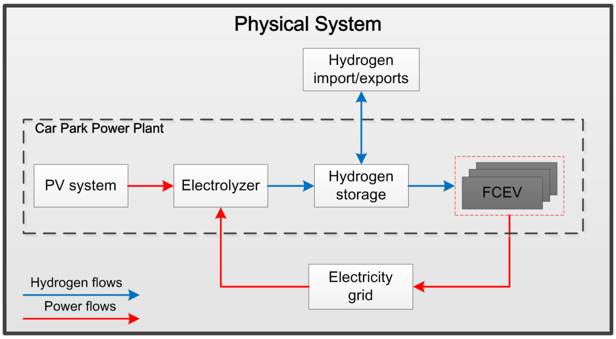


Figure 7.1: CPPP: Description of physical system

7.2.2. Actor network

The physical components and flows explained above are controlled and influenced by the actors in the system. The **aggregator** controls the operations in the CPPP: it operates the electrolyzer and the plugged in vehicles, and also imports and exports hydrogen. Most importantly, it buys and sells electricity in the day-ahead market. As the entity managing the hydrogen system and vehicle-to-grid operations, it is also responsible of the financial flows.

Drivers are the actors that own and use the FCEVs on a daily basis. They make decisions on the driving, refilling and plug-in behavior. As vehicle owners, they also decide how to participate as vehicle-to-grid power suppliers. As mutually dependent actors, aggregators and drivers need to have an agreement regarding the operation of their vehicles.

Other actors that might be relevant in this system are the car park operator or the participants of the day-ahead market. We do not consider the car park operator because the focus remains on the hydrogen system and vehicle-to-grid operations and not the use of the car park for parking purposes. Since the physical system boundary is defined by the car park, the rest of the system - including the actors in the wholesale market - is not considered.

7.2.3. Institutions

The institutions used to govern the interactions between the physical system and actors are described according to the level they belong to.

Level 2: Policies

Policies are not considered explicitly in this research. However, we assume some regulatory measures exist that allow vehicle-to-grid and hydrogen conversion and storage within a parking facility. We also envision the CPPP embedded in a system in transition towards a low-carbon energy future. Therefore, we assume there are relevant policies to encourage the implementation of flexibility resources. Following the current trends in Europe (European Commission, 2016), we also assume that the participation of consumers and prosumers in the electricity system is established successfully.

Level 3: Play of the game

Ownership The aggregator is the owner of the physical components of the CPPP system, including the solar panels, electrolyzer and hydrogen storage and refilling system. It is also responsible for the V2G infrastructure, namely the discharging poles installed in the car park. As the owner, the aggregator is responsible for the investments. The drivers are considered to be the vehicle owners themselves.

Electricity market The electricity market in place is the typical one liberalized power systems, where multiple participants buy and sell electricity freely. We only consider the day-ahead market, although the CPPP could participate in the intraday or balancing markets. As mentioned earlier, we do not consider the actors or interactions within these markets, but only use the market prices to explore the performance of the CPPP. Because there are rules that establish the minimum volume increment in day-ahead markets, we assume that small consumer/prosumer can participate only when aggregated. Therefore, fuel cell vehicles can only provide V2G in the electricity market through an aggregator.

Vehicle-to-grid contracts As discussed in Chapter 5, bilateral contracts are the type of governance chosen for vehicle-to-grid supply. In this system, we only consider price-based vehicle-to-grid contracts. This means that drivers can provide electricity freely without having plug-in duration requirements. Moreover, drivers allow the aggregator to use the fuel cell car only when the market price is above their desired *minimum V2G price*. The contract also specifies the maximum volume of energy an aggregator may use in each instance. The contract parameters are described in more detail in the next section.

Level 4: Prices and quantities

Bid and offer price The aggregator's decisions to sell/buy electricity are made based on the day-ahead market prices. When it is below a certain threshold, the aggregator buys power to operate the electrolyzer at maximum capacity. When the price is above a certain minimum value, the aggregator sells vehicle-to-grid power at a fixed aggregated volume.

V2G remuneration The remuneration for V2G is defined by the contract parameters and the actual market price. This is explained in more detail in the following section. The contract ensures that a vehicle is only used when the driver can be remunerated at least for the cost of producing electricity with the fuel cell. Therefore, it depends on the price of hydrogen paid for refilling.

Hydrogen price The price of hydrogen is based on the cost of producing it in the CPPP. Hydrogen can be produced using the solar panels and by buying electricity from the day-ahead market. Therefore the costs partly depend on the costs incurred in the day-ahead market. We use the capital costs and the operation and maintenance costs to determine the system levelized cost of hydrogen (SLCoH). This cost is used as the hydrogen price, with no profit margin. We assume the same price for any imports and exports of hydrogen.

7.3. Agent-based model description

In this section, we describe the agent-based model built, following the ODD protocol (Grimm et al., 2006). After the *Overview* and *Design concepts* sections, we describe the elements of the *Details* in separate subsections and in a different order. More details of the ODD protocol can be found in Appendix B.

7.3.1. Overview

As Fig.7.2 shows we conceptualize and formalize the system described above as an agent-based model. Thus, the physical system and its operation are modeled, as well as the actors and their actions. The contracts and other institutions are formalized as rules and conditions. To account for all transactions, prices are calculated as described previously.

Purpose

The modeling question addressed in this chapter is: *"How do price-based contract parameters and the V2G operating strategy influence the profit potential for heterogeneous drivers and the aggregator, in electricity systems with high renewable energy penetration?"*.

To do this, we explore how the implementation of price-based contracts (PBC) and the aggregator's strategies influence the profit potential in electricity markets with high wind penetration. In this chapter, we focus mainly on the economic performance from the perspective of drivers, but also determine the aggregator's performance. Since drivers are heterogeneous in their driving needs and parking use profiles, we explore how the profit is related to their characteristics.

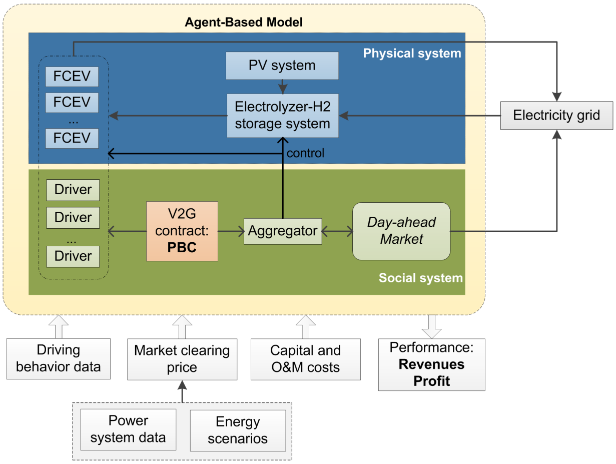


Figure 7.2: Model concepts

We represent the actors as agents and the physical components as objects. We use the model to simulate the operation of the CPPP, combining the processes in the physical system and the actions of the actors. The main actors are the drivers and the aggregator. Although it is part of the social subsystem, the day-ahead market is represented as a simple agent that gives information on the market clearing prices.

To define heterogeneous driving schedules (arrival and departure times, and daily driving distances) we use probability distributions derived from driving data (Centraal Bureau voor de Statistiek (CBS) & Rijkswaterstaat (RWS), 2015). The market clearing prices are calculated externally using power system data and historical wind and solar generation profiles (ENTSO-E, 2017; Open Power System Data, 2017). Using the market prices, the aggregator makes decisions to buy/sell electricity in the day-ahead market. Whenever V2G has been scheduled, the aggregator uses the V2G contract parameters to dispatch power using FCEVs. Capital and operation and maintenance (O&M) costs are used to determine the price of hydrogen in the system, which influences the participation of drivers in the market and their profitability. For all agents, the revenues, costs, and profits are calculated as the main measure of performance.

Agents and objects

Driver agent This agent represents both the characteristics of the driver and the vehicle's technical properties. The main variables are listed in Table 7.1. Each driver agent has a parking profile that indicates whether it uses the car park during 'work' or 'home' hours. To define the conditions for V2G participation, each agent owns a

V2G contract object (Table 7.6). For the complete list of variables, see Table B.1 in Appendix B.

Table 7.1: Driver agent variables

Variable	Description	Data type
	Driver properties	
`arrival`	Arrival time at car park	Integer
`departure`	Departure time from car park	Integer
`distance`	Daily distance traveled	Integer
`drivingSchedule`	Standard arrival and departure times	Integer (list)
`pProfile`	Parking profile	String
`refillCondition`	Decimal fraction used to decide whether or not to refill	Float
`isAdjustBehavior`	State indicating whether the driver is changing its behavior	Float
`minFuelDriving`	Daily fuel need for driving	Float
`fuelSF`	Safety factor to determine daily fuel need for driving	Float
`contract`	Vehicle-to-grid contract that specifies conditions for participation	Object
	Vehicle properties and states	
`fuelAvailability`	Decimal fraction indicating the fuel available for V2G	Float
`fuelMax`	Maximum hydrogen capacity in vehicle's tank	Float
`hydrogenLevel`	Current level of hydrogen	Float
`isDriving`	State indicating whether the driver is using the vehicle to drive	Boolean
`isRefilling`	State indicating whether the driver is using the vehicle to refill	Boolean
`isHere`	State indicating whether the driver is in the parking garage	Boolean
`isPluggedin`	State indicating whether the vehicle is plugged in	Boolean
`isV2G`	State indicating whether the vehicle is being used for V2G	Boolean
`isV2G_t`	List of V2G states, where True = 1 and False = 0	Integer (list)
`Hrefill`	Amount of hydrogen refilled in current time step	Float
`pFCEV`	Amount of power being delivered using the vehicle in current time step	Float
`startUps`	Total number of startUps	Float
	Techno-economic variables of vehicle use	
`energyCost`	Cost of producing 1 kWh of electricity using hydrogen	Float
`fuelCost`	Cost of hydrogen	Float
`costV2G`	Cost of supplying electricity using vehicle in current time step	Float
`profitV2G`	Profit from V2G supply	Float
`revenuesV2G`	Revenues for V2G supply	Float
`totalNetProfitV2G`	Total net profit at the end of simulation	Float
`totalPluginHours`	Total plug-in hours at the end of simulation	Float
`totalProfitV2G`	Total profit at the end of simulation	Float
`totalRevenuesV2G`	Total revenues at the end of simulation	Float
`totalVolume`	Total volume of electricity supplied at the end of simulation	Float

Aggregator agent The aggregator participates in the day-ahead market to sell V2G or buy electricity to operate the electrolyzer. The aggregator owns an **Electrolyzer-Hydrogen storage system object** as well as a **PV-system object**. Table 7.2 shows the main list of the aggregator's variables. See Table 7.3 for the storage system variables, and Table 7.4 for the PV system properties. The full list of variables is in Table B.2 of Appendix B.

Day-ahead market agent As shown in Table 7.5 the day-ahead market is a simple agent that provides every day the market clearing prices for the following day, and hourly electricity prices for the current day.

Table 7.2: Aggregator agent variables

Variable	Description	Data type
	Contracted drivers	
`drivers_list`	List of contracted drivers	Object (list)
`driversH_list`	List of contracted drivers with Home profile	Object (list)
`driversW_list`	List of contracted drivers with Work profile	Object (list)
	DAM participation and V2G	
`dispatchableFCEVs`	Number of vehicles that can be used for V2G	Integer
`dispatchedFCEVs`	Number of vehicles used for V2G	Integer
`dischargerPoles`	Number of 4-point discharger poles	Integer
`dischargers`	Number of dischargers	Integer
`market`	Day-ahead market	Object
`maxBuyPrice`	Maximum buy price in day-ahead market	Float
`minSellPrice`	Minimum sell price in day-ahead market	Float
`opBuyVol`	Actual electricity used from buy orders	Float
`opSellVol`	Actual electricity dispatched from sell orders	Float
`PoP`	Preferred operating point of individual FCEVs	Integer
`totalCostsDA`	Total costs from day-ahead market	Float (list)
`totalCostsV2G`	Total operational costs of V2G at the end of simulation	Float (list)
`totalProfitV2G`	Total profit of V2G operation	Float (list)
`totalRevenuesDA`	Total profit from day-ahead market	Float (list)
`totalV2G`	Total V2G supplied in day-ahead market during simulation period	Float
	PV-Electrolyzer-Storage system	
`hSystem`	Hydrogen conversion and storage system	Object
`PVsystem`	PV system	Object
`profitHS_t`	List of profit made with hydrogen system	Float (list)
`revenuesHS_t`	List of revenues realized with hydrogen system	Float (list)
`totalProfitHS`	Total profit from hydrogen system at the end of the simulation	Float
`totalRevenuesHS`	Total revenues from hydrogen system at the end of the simulation	Float
	Total Costs	
`TCel`	Total costs electrolyzer	Float
`TChs`	Total costs hydrogen storage	Float
`TCc`	Total costs compressor	Float
`TCd`	Total costs dispenser	Float
`TCrw`	Total costs rainwater collector	Float
`TCro`	Total costs reverse osmosis	Float
`TCpv`	Total costs PV system	Float
`TCdis`	Total costs V2G discharger poles	Float
`SLCOH`	System levelized cost of hydrogen	Float

V2G contract object Price-based contracts between drivers and the aggregator allow the aggregator to know when the FCEV can be used for V2G. As shown in Table 7.6, the contract also specifies the remuneration structure: the driver receives the `minPrice` and the `driverMargin`. Moreover, there is an annual contracting fee for V2G participation, to be paid at the end of the year.

Process overview

Fig.7.3 illustrates an overview of the processes in the agent-based model. The aggregator's actions are mostly based on the steps indicated in the USEF framework (USEF Foundation, 2016). The overall process is described shortly in Table 7.7, followed by the model narrative from the aggregator and driver's point of view.

Table 7.3: Electrolyzer-Hydrogen system object variables

Variable	Description	Data type
`elecCapacity`	Electrolyzer capacity	Float
`fuelPrice`	Fuel level that the aggregator has to guarantee to driver after V2G	Float
`HSlevel`	Level of hydrogen in the hydrogen storage system	Float
`HSmax`	Hydrogen storage capacity	Float
`HSmin`	Minimum capacity of the hydrogen storage system	Float
`Hexport`	Hourly hydrogen exported	Float
`Himport`	Hourly hydrogen imported	Float
`Hprod`	Hourly hydrogen produced (total)	Float
`HprodDAM`	Hourly hydrogen produced (day-ahead market)	Float
`HprodPV`	Hourly hydrogen produced (PV)	Float
`Hrefill`	Hourly amount of hydrogen refilled by vehicles	Float
`pElecDAM`	Power electrolyzer (DAM)	Float
`pElecPV`	Power electrolyzer (PV)	Float
`pElec`	Total power of electrolyzer	Float
`totalHimport`	Hydrogen imported at the end of the year	Float
`totalHexport`	Hydrogen exported at the end of the year	Float
`totalHprod`	Level of hydrogen in the hydrogen storage system	Float
`totalHrefill`	Level of hydrogen in the hydrogen storage system	Float

Table 7.4: PV system object variables

Variable	Description	Data type
`PVcapacity`	PV system capacity	Float
`PVpower`	Hourly PV generation	Float
`PVprofile`	Hourly PV capacity factor profile	Float

Table 7.5: Day-ahead market agent variables

Variable	Description	Data type
`DAprices_t`	Day-ahead market prices for the following day	Float (list)
`minVol`	Minimum volume in electricity market	Float
`price`	Hourly market price	Float

Table 7.6: Vehicle-to-grid contract object variables

Variable	Description	Data type
`contrCost`	Contracting cost: annual fee to participate in vehicle-to-grid through the aggregator	Float
`driverMargin`	Profit margin that driver gets for the difference between the market price and the *minPrice*	Float
`guarFuel`	Fuel level that the aggregator has to guarantee to driver after V2G	Float
`minPrice`	Minimum price that the driver is willing to accept for providing V2G	Float

Aggregator Every day at the `plan` stage, the aggregator makes decisions for buying and selling V2G. It is assumed that the aggregator has perfect foresight and knows the prices beforehand. If prices are expected to be low, the aggregator places bids to buy electricity. The next day, in the `operate` step the aggregator follows the plan based on accepted offers/bids. When V2G is sold, the aggregator operates the available FCEVs to deliver electricity. To dispatch the vehicles, the aggregator can use different rules.

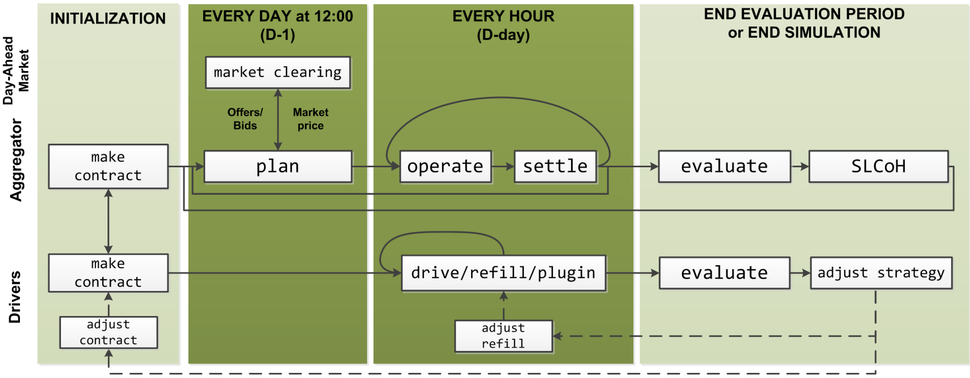


Figure 7.3: Process overview per agent type

Table 7.7: Process overview description

Initialization	When the agents are created at the initialization, a contract is made for each driver agent, in which the `minPrice`, `guarFuel`, `evalPeriod` and `dMargin` are defined. The aggregator provides the `contrCosts` to each driver agent based on the V2G infrastructure costs and number of drivers.
Every day at 12:00	Every day at noon, during the market clearing, the day-ahead market agent informs the prices for the next day. Using that information, the aggregator places bids or offers on the market.
Every Hour	Every hour, drivers can perform actions with their vehicle: drive, refill, plug-in. The aggregator's hourly operations take place according to the results of the previous day. Thus, the scheduled electrolyzer/vehicle-to-grid operation takes place.
End evaluation period	After each evaluation period, the aggregator calculates the average performance of drivers with Home and Work profiles and provides the information to the driver agents. The drivers evaluate their performance and adjust the refilling strategy accordingly. The system levelized cost of hydrogen is calculated based on the hydrogen produced after each period and the total costs that correspond to the fraction of the year. Therefore, the hydrogen price is updated after every evaluation period, influencing the drivers' `minPrice` when they refill.
End simulation	A final evaluation is carried out at the end of the simulation.

It can either choose in ascending `startUps` order or descending `fuelAvailability` order. Every hour, at the `settle` step the revenues and costs for the aggregator are calculated, both for the hydrogen system and V2G operation. The payment to drivers is also executed in this step. The operation of the PV system and hydrogen system are performed also in the `operate` step of the aggregator. In the `evaluate` step, the aggregator calculates its performance during the evaluation period, as well as that of the drivers. It communicates the average profits earned by the drivers. After the evaluation, it recalculates the hydrogen price in the `SLCoH` step. The same is done at the end of the simulation.

Driver Every day, driver agents `drive` in and out of the car park for commuting purposes. Upon arrival, drivers park and `plugin` to the grid, if there are enough discharging points available. Once plugged in, the `fuelAvailability` is used to calculate the contract parameter `driverMargin`. Then, based on the V2G schedule, the aggregator may use the vehicles taking the contract parameters into account. Drivers can `refill` their vehicle either after plug-in or before leaving the car park. This is based on the `refillCondition` and the hydrogen level. Drivers receive their remuneration for the V2G supplied in the aggregator's `settle` step. In the `evaluate` step, they learn about their performance and the average drivers' profit. In the `adjust strategy` step, and if their performance is lower than the average, drivers adjust their behavior either through `adjust contract` or `adjust refill`.

Causal loops

To analyze how the interactions between drivers and the aggregator affect their performance, we visualize their relationship between in causal loop diagrams. Figure 7.4 shows the driver agents' variables, and how they are related to the aggregator. Figure 7.5 shows the aggregator's variables and the relationship with the drivers' variables.

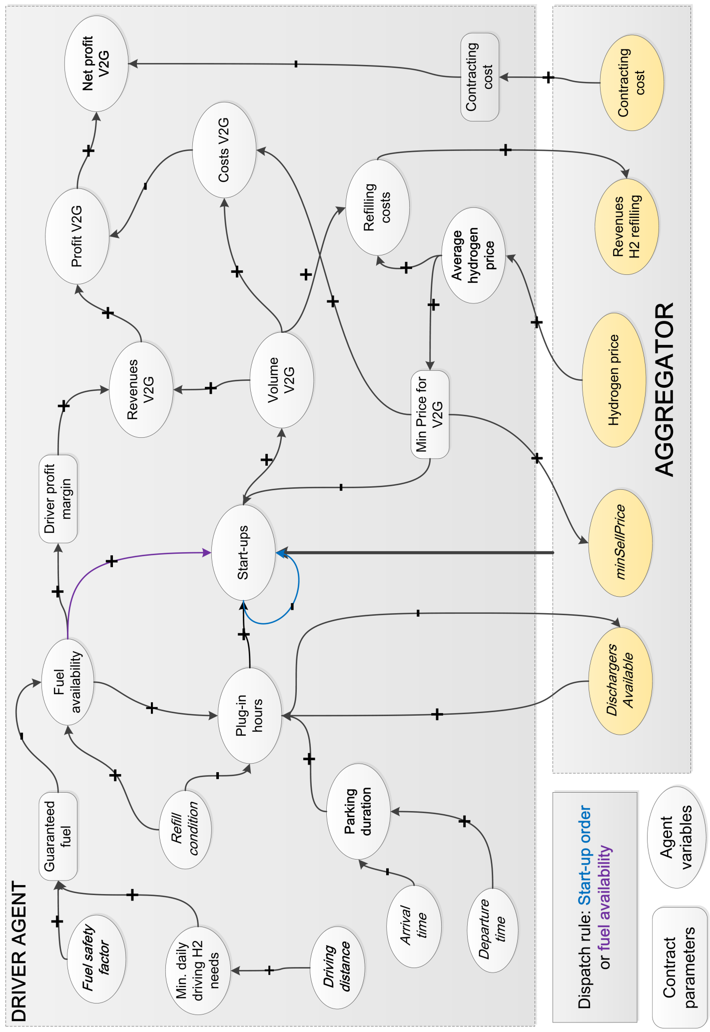


Figure 7.4: Causal loop diagram: Driver

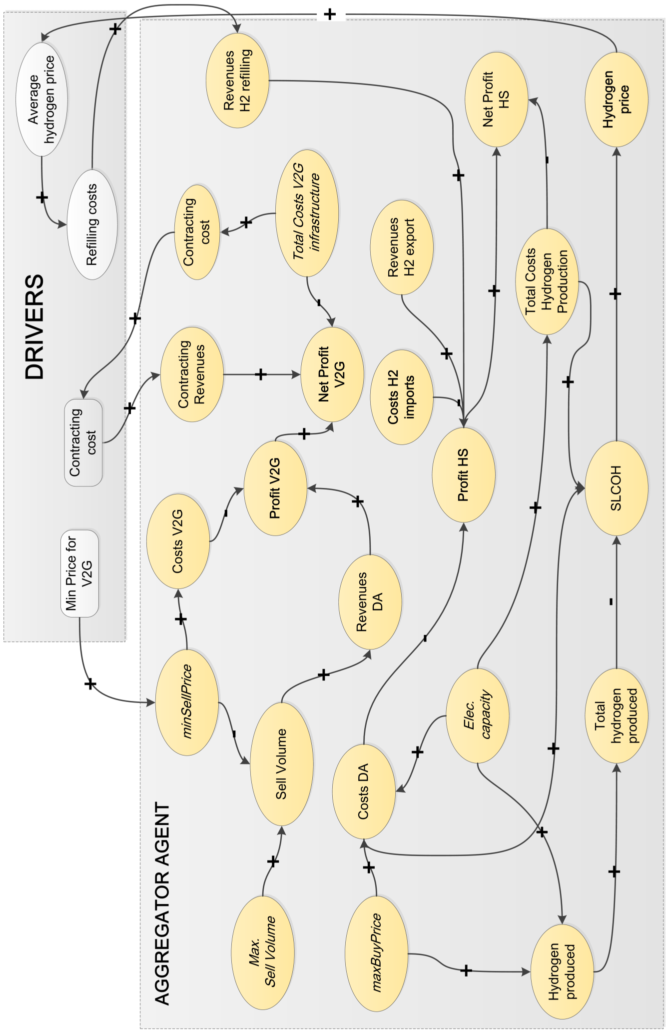


Figure 7.5: Causal loop diagram: Aggregator

7.3.2. Design concepts

In this section we explain some of the design concepts of the agent-based model.

Emergence The outputs of the aggregator are the annual profits from V2G and the hydrogen system. For the driver, the main outputs are the annual profit, the amount of V2G supplied and the number of start-ups. At the system level, the main output is the amount of V2G sold in the electricity market.

While the amount of hydrogen produced by the aggregator is predictable - it only depends on the market price, and export is possible - the amount of V2G provided can vary. The aggregator will always offer V2G based on the *average* `minPrice` of all drivers at the time and a constant assumed aggregated capacity. However, on the day of dispatch, aggregated capacity may vary. This is because the `minPrice` of available vehicles may be below the average calculated the previous day. Additionally, the available capacity of FCEVs may quickly decline when many consecutive hours of V2G are scheduled.

The vehicles being operated for V2G depend on the dispatch rule, the other vehicles available at the time, and the own vehicle's state. For any single driver agent, the annual profit from V2G is not predictable. The average drivers' profit and total volume of V2G supplied are emergent properties of the model.

For the same reasons, the total amount of hydrogen refilled at a certain time step is not predictable and can be considered an emergent property. The total amount of hydrogen refilled during the year may be more predictable, as well as the total profit from the hydrogen system.

Fitness Driver agents have the net profit as a measure of their objective. Therefore, after each evaluation period, the driver compares its performance to other drivers with the same parking profile. When its performance is lower, it will change its behavior to try to increase the net profit in the next period. For the aggregator, the net profit is also a measure of its objective. However, the aggregator does not change his behavior based on this measure.

Sensing The variables of the environment are sensed at the evaluation step. Driver agents receive from the aggregator the average profit of all drivers that share the same parking profile.

Interaction Although driver agents do not interact actively with other driver agents, they are influenced by their performance. By comparing their own performance to the average, they make decisions on whether to change their refilling behavior. The aggregator interacts with drivers by providing information and by remunerating them based on their V2G service.

Prediction Drivers do not predict future conditions, but change their behavior in hopes that their profit improves. The aggregator does not predict future availability or future prices. It is assumed to have perfect foresight with regards to market prices.

Adaptation Drivers adapt by changing their refilling preferences and behavior in two ways. One way is to increase the refilling condition: the minimum % of `fuelAvailability` required to plug in the vehicle. Whenever there is less fuel than this value, the driver will refill before plugging in. The other way is by reducing the fuel safety factor `fuelSF`, which decreases the `guarFuel` contract parameter. Practically, this increases the fuel availability directly without changing the refilling behavior. Both strategies are meant to increase the `fuelAvailability` and therefore the `driverMargin` at plug-in. A higher fuel availability also increases the chances of providing more vehicle-to-grid power.

Stochasticity Stochasticity is introduced in different ways. Initial states such as the hydrogen storage level or the drivers' hydrogen level are defined randomly between two bounds. Drivers' properties are also initialized with some randomness: 1) different driving schedules are assigned every time using a probability distribution derived from data, and 2) the parking profile is assigned randomly. Variability is also introduced in drivers so that their driving schedules may vary every day in + or - one hour. When drivers change their refilling strategy, they choose between the two options at random. Finally, the order in which driver agents are activated in the model is also random.

Collectives An aggregated vehicle pool is represented by the `drivers_list`; a list of driver agents that the aggregator has of the contracted drivers. This is used to calculate the average `minSellPrice` in the day-ahead market. Moreover, separate groups for the Home and Work profile drivers are used (`driversH_list`, `driversW_list`) to determine the performance of agents that use the CPPP at different time frames.

Observation To observe the internal dynamics and system-level behavior, several outputs are gathered. At the system-level, we follow the hydrogen balance: amount of hydrogen produced, refilled, imported and exported. We also follow the amount of V2G supplied (and not supplied). We also follow the changing hydrogen price and minimum sell price in the market. At the individual level, we follow the agents' performance, we calculate the revenues, costs, and profit at every time step. Additionally, to understand the drivers' performance we also follow the `AvgHydrogenPrice`, the adjust strategy (`adjust refill` and `adjust contract`), the `driverMargin` and the volume of V2G supplied.

7.3.3. Submodels

In this section we provide details about the submodels of the agents. We present the relevant equations using a scientific notation to show how the different variables are calculated at every time step. The list of variables used can be found in the Nomenclature in Appendix B.4.

Driver: `Make contract`

The driver's profit margin indicates how the difference between the contractual `minPrice` and the market price is shared between the aggregator and the driver. In this model, the profit margin is calculated every day when the driver connects the vehicle, as a function of the fuel available at the time. As Fig. 7.6 shows, fuel availability indicates the percentage of fuel that could be used for V2G, and depends on the amount of fuel at plug-in, and the contractual guaranteed fuel level. This is done to reward higher fuel availability, as it increases the amount of energy available to the aggregator.

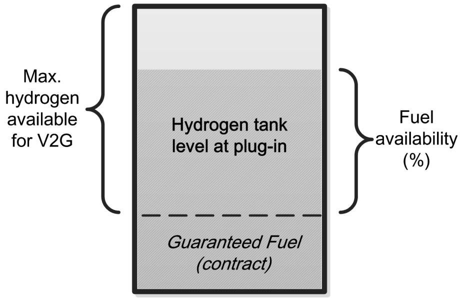


Figure 7.6: Concept of fuel availability

Using 0.75 as the highest profit margin possible for the aggregator and for the driver, we define a range of profit margin between 0.25 and 0.75. Within this range, the profit margin for the driver m_i^{V2G}, is defined as a logarithmic function that indicates the profit margin at different availability levels (`fuelAvailability`). A logarithmic function is used instead of a linear function to reward drivers increasingly at higher fuel availability. This is done to mimic the discount in monthly mobile data plans, were the price per 100MB changes following a power or logarigthmic function. This price decreases sharply based on the data plan size. However, as the data plan increases, the discount again decreases.

$$m_{it}^{V2G} = \begin{cases} 0.25 & \text{if } FA_{it} < 0.25 \\ 0.4551 \cdot ln(FA_{it}) + 0.8809 & \text{if } 0.25 \leq FA_{it} < 0.75 \\ 0.75 & \text{if } FA_{it} \geq 0.75 \end{cases} \tag{7.1}$$

All agents: `Evaluate`

Aggregator: Revenues and costs The total costs for the aggregator over a period T are composed of the costs in the day-ahead market and the costs of V2G remuneration.

$$c_k = \sum_{t=0}^{T} (c_{kt}^{DA} + c_{kt}^{V2G}) \tag{7.2}$$

$$c_{kt}^{DA} = p_t^{DA} \cdot P_t^{el,DA} \cdot \Delta t \tag{7.3}$$

$$c_{kt}^{V2G} = \sum_{i=0}^{N_{fcev}} P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot (p_i^{V2G} + (p_t^{DA} - p_i^{V2G}) \cdot m_i^{V2G}) \tag{7.4}$$

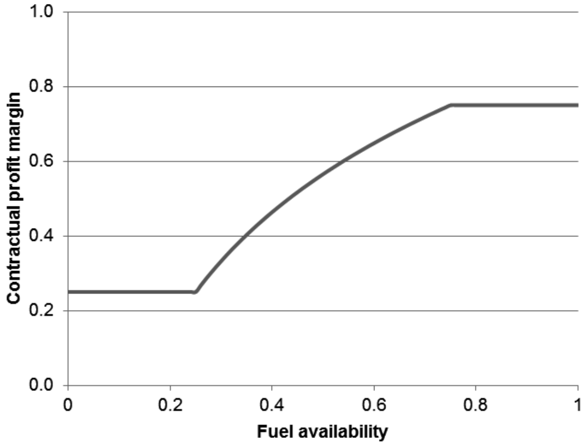


Figure 7.7: Driver margin as a function of fuel availability

The total revenues for the aggregator are calculated by adding the revenues from the day-ahead market and the revenues from the hydrogen refilling station.

$$r_k = \sum_{t=0}^{T} (r_t^{DA} + r_t^{HS}) \tag{7.5}$$

$$r_{kt}^{DA} = \sum_{i=1}^{N_{fcev}} p_t^{DA} \cdot P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \tag{7.6}$$

$$r_{kt}^{HS} = \sum_{i=1}^{N_{fcev}} p_{t,H2} \cdot H_{it}^{ref} \cdot y_{it} \tag{7.7}$$

Thus, the gross profit from V2G can be defined as:

$$profit_k^{V2G} = \sum_{t=0}^{T} (r_{kt}^{DA} - c_{kt}^{V2G}) \tag{7.8}$$

$$profit_k^{V2G} = \sum_{i=0}^{N_{fcev}} P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot (p_t^{DA} - p_i^{V2G}) \cdot (1 - m_{it}^{V2G}) \tag{7.9}$$

The gross profit realized from the hydrogen refilling system is expressed as:

$$profit_k^{HS} = \sum_{t=0}^{T} (r_{kt}^{HS} - c_{kt}^{DA}) \tag{7.10}$$

Driver: Revenues and costs The total costs for every driver i over a period T consist of the cost of V2G supply and the refilling costs.

$$c_i = \sum_{t=0}^{T} (c_{it}^{V2G} + c_{it}^{ref}) \tag{7.11}$$

$$c_{it}^{V2G} = P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot c_{V2G} \tag{7.12}$$

$$\text{where}: c_{V2G} = \frac{p_{t,H2}}{HHV \cdot \eta_{FC}} + \frac{CC_{FC}}{LT_{FC}} \cdot 0.5 \tag{7.13}$$

It is assumed that the minPrice in the contract (p_i^{V2G}) equals the cost of producing 1 kWh V2G c_{V2G}. This cost can change based on the price of hydrogen purchased at time t, $p_{t,H2}$.
Therefore:

$$c_{it}^{V2G} = P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot p_i^{V2G} \tag{7.14}$$

The refilling costs are:

$$c_{it}^{ref} = p_{t,H2} \cdot H_{it}^{ref} \cdot y_{it} \tag{7.15}$$

The revenues for a driver over a period T are those corresponding to the V2G participation.

$$r_i = \sum_{t=0}^{T} r_{it}^{v2g}\ , \tag{7.16}$$

$$\text{where: } r_{it}^{V2G} = P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot (p_i^{V2G} + (p_t^{DA} - p_i^{V2G}) \cdot m_{it}^{V2G}) \tag{7.17}$$

$$profit_i^{V2G} = \sum_{t=0}^{T} (r_{it}^{V2G} - c_{it}^{V2G}) \tag{7.18}$$

$$profit_i^{V2G} = \sum_{t=0}^{T} P_{it}^{fcev} \cdot x_{it} \cdot \Delta t \cdot (p_t^{DA} - p_i^{V2G}) \cdot m_{it}^{V2G} \tag{7.19}$$

Removing the contracting costs, the net profit for a driver is defined as:

$$netprofit_i^{V2G} = profit_i^{V2G} - c_i^{contract}) \tag{7.20}$$

$$c_i^{contract} = \frac{TC_{V2Gd}}{N_{fcevs}} \tag{7.21}$$

Drivers: `Adjust strategy`
Drivers change their behavior and preferences regarding the fuel to increase revenues. Although it is not possible to predict or ensure an increase in revenues, they intuitively try to increase the hydrogen available for V2G. Doing this has two effects: 1) Indirectly increases the chances of being used for V2G more often, 2) Directly increases the driver's profit margin (m_{it}^{V2G}).

Increasing the hydrogen available for V2G can be done in two ways. Drivers randomly choose one option, and if it is not possible they check the next option:

1. **`adjust refill:`** After arrival, the `fuelAvailability` is checked, and if it is lower than a certain `refillCondition`, the driver will refill before plugging in. Drivers can increase the `refillCondition` to ensure there is enough energy for V2G. This is possible when the `refillCondition` is lower than the maximum

value (refillCondition < MAX_REFILLCONDITION). It is calculated as indicated in equation 7.22.

$$\begin{aligned} \texttt{refillCondition} &= \texttt{refillCondition} + \\ \texttt{REFILL\_CHANGE} &\cdot (\texttt{MAX\_REFILLCONDITION} - \texttt{refillCondition}) \end{aligned} \tag{7.22}$$

2. **adjust contract**: In the contract, the guaranteed fuel after V2G (guarFuel) is defined as the minimum hydrogen needed for 1 day of driving (minFuelDriving), times a safety factor (fuelSF). The fuelSF can be further reduced to allow the aggregator to use more energy from the vehicle. This is possible when it is above the minimum value (fuelSF > MIN_FSF), following equation 7.23. The updated value is then used to compute the guarFuel parameter.

$$\texttt{fuelSF} = \texttt{fuelSF} - \texttt{FSF\_CHANGE} \cdot (\texttt{fuelSF} - \texttt{MIN\_FSF}) \tag{7.23}$$

Aggregator: SLCoH

To calculate the system levelized cost of hydrogen over a year, we calculate the total costs of the system taking into account the following components: 1) Electrolyzer, 2) PV system, and 3) Hydrogen storage and refilling system (Hydrogen storage, compressor, dispenser, reverse osmosis, rainwater collector). The equations of the total costs of each component can be found in Appendix B.

$$SLCoH = \frac{cost_{power} + TC_{el} + TC_{PV} + TC_{HS} + TC_{c} + TC_{d} + TC_{rw} + TC_{ro}}{production_{H2}} \tag{7.24}$$

where

$$cost_{power} = c^{DA} = \sum_{t=0}^{8760} p_t^{DA} \cdot P_t^{el,DA} \cdot \Delta t \tag{7.25}$$

$$production_{H2} = \sum_{t=0}^{8760} P_t^{el} \cdot \Delta t \cdot \frac{\eta_{el}}{HHV} \tag{7.26}$$

Moreover, the aggregator also pays for the total costs of V2G dischargers (dis) for the V2G infrastructure:

$$TC_{dis} = CC_{dis} + OMC_{dis} \tag{7.27}$$

$$CC_{dis} = CC_{dis}^{unit} \cdot N_{dis} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{dis}}}{((1 + WACC)^{LT_{dis}} - 1)} \tag{7.28}$$

$$OMC_{dis} = CC_{dis}^{unit} \cdot N_{dis} \cdot OMC_{dis}^{\%} \tag{7.29}$$

7.3.4. Input parameters and data

Estimated wholesale electricity prices

An important input for the model are day-ahead market prices. The CPPP system envisioned is embedded in a future electricity system with high variable renewable energy penetration. Since the current electricity prices cannot be used for this type of analysis, we estimate the market clearing prices in systems with different levels of renewable energy. The hourly prices for the whole year are calculated in a separate model, and then introduced as a time series input. The data used to calculate the prices are from Germany, due to the availability of information and the already high renewable energy penetration levels.

Energy scenarios We calculate the hourly day-ahead market prices for three energy scenarios with the same renewable energy penetration scenario and increasing carbon allowance prices (Table 7.8). The energy mix used in the scenarios is shown in Table 7.9. The installed generation capacities in Germany in 2017 (Open Power System Data, 2017) are used as a base case, and the energy mix in 2050 is changed according to one of the decarbonization pathways for Germany presented by (Henning & Palzer, 2015). This scenario[1] considers an accelerated exit of coal power plants by 2040, a reduction of CO_2 by 80%, a mix of electric vehicles, fuel cell vehicles, and compressed natural gas vehicles, as well as ambitious targets in energy in the built environment. In terms of the energy mix, it indicates the following projections for 2050:

- Solar PV: 122 GW
- Wind (offshore + onshore): 171 GW
- Coal and lignite power plants decommissioned
- Nuclear power plants decommissioned
- Total capacity of CCGT gas, Gas Turbines, CHP: over 80 GW

The final point involves a steep increase in the installed capacity of CCGT and Gas Turbines. For our study, we assume that 50% of the capacity corresponding to the removed coal and lignite plants is replaced by increased CCGT and Gas turbines[2]. We assume that the other 50% would be covered by fuel cell electric vehicles and other plug-in electric vehicles. This would correspond to 2.5 million fuel cell vehicles, with a capacity of 10kW.

Table 7.8: Energy scenarios

Energy scenario	Renewable energy	Carbon allowance price, €/ton
80SWLC	80% Solar PV + Wind	6.00
80SWMC	80% Solar PV + Wind	30.00
80SWHC	80% Solar PV + Wind	60.00

The day-ahead market prices are calculated for the three energy scenarios described above: 80SWLC, 80SWMC, 80SWHC.

Supply curve First we build the supply curve, using the German power plant data capacities in (Open Power System Data, 2017). To do this, the marginal cost of each power plant mc_{pp} is calculated as follows, based on the fuel type used:

$$mc_{pp} = \frac{c_{fuel} + c_{carbon} \cdot v_{carbon,fuel}}{E_{fuel} \cdot \eta_{pp}}, [€/\text{MWh}] \tag{7.30}$$

[1] 80/amb/mix/acc.

[2] The capacities of all CCGT power plants running with Natural gas are increased proportionally, as well as the capacities of Gas Turbines running on natural gas and oil

Table 7.9: Energy mix for electricity generation

Fuel type	**Base case 2017**		**80SW Renewable Energy Mix**	
	Capacity, MW	%	**Capacity, MW**	%
Biomass & biogas	858.70	0.4	858.70	0.2
Hard coal	27,426.00	14.0	0	0
Hydro	13,246.30	6.8	13,246.30	3.6
Lignite	21,164.40	10.8	0	0
Natural gas	26,475.20	13.5	47,384.67	13.0
Nuclear	10,800.00	5.5	0	0
Oil	4,221.40	2.2	7,607.13	2.1
Waste	1,633.50	0.83	1,633.50	0.4
Solar	40,294.00	20.6	122,000.00	33.5
Wind	49,569.00	25.3	171,000.00	47.0
Total	195,688.50	100	363,730.30	100

For each fuel type, fuel costs per MWh and carbon costs per MWh were calculated using several sources for fuel costs (BP, 2017; Khan, Verzijlbergh, Sakinci, & De Vries, 2018; UK Department of Business Energy & Industrial Strategy, 2018) and carbon emission coefficients (U.S. EIA, 2016).

Table 7.10: Fuel costs

Fuel type	**Fuel cost, €/MWh**	**Carbon cost, €/MWh**			**Total fuel cost, €/MWh**		
		80SWLC	**80SWMC**	**80SWHC**	**80SWLC**	**80SWMC**	**80SWHC**
Biomass & biogas	17.28	0.00	0.00	0.00	17.28	17.28	17.28
Hard coal	10.37	2.12	10.61	21.23	12.49	20.98	31.60
Hydro	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Lignite	10.37	2.00	10.00	20.00	12.37	20.37	30.37
Natural gas	25.27	1.09	5.43	10.87	26.36	30.70	36.14
Nuclear	4.46	0.00	0.00	0.00	4.46	4.46	4.46
Oil	36.16	1.95	9.75	19.50	38.11	45.91	55.66
Waste	0.00	0.85	4.27	8.53	0.85	4.27	8.53
Solar	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wind	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Market clearing prices as time series data The residual demand is determined with the hourly demand and the PV and wind generation (Open Power System Data, 2017). Since there is an increase in wind generation capacity, the hourly generation is calculated based on the increased capacity and the hourly wind generation profile[3] from 2017. The installed PV capacity remains the same.

The hourly residual demand and the supply curve are used to determine the hourly market price by approximation. The hourly prices for each energy scenario are used as

[3]The energy generated as a percentage of the installed capacity

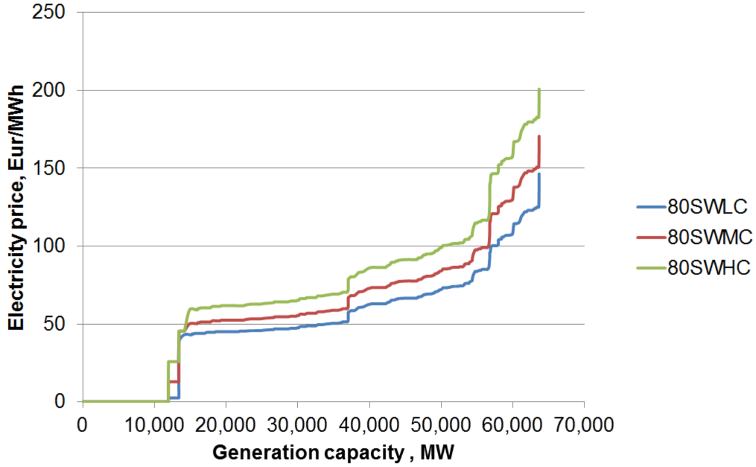


Figure 7.8: Supply curve

an input in the simulation experiments. To better observe the differences in price levels, we construct price-duration curves for each scenario, as shown in Fig. 7.9.

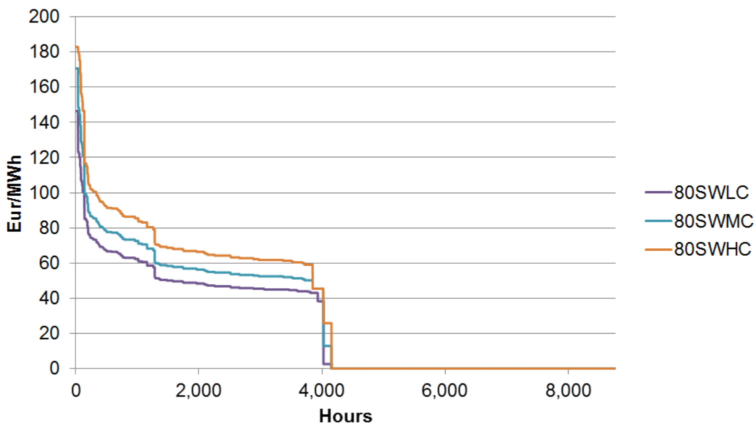


Figure 7.9: Price-duration curve for the three energy scenarios

Driver data

The driving data inputs are the same as in Chapter 6. However, different parking profiles were created in this model: `Home` and `Work`. The first has the same type of parking behavior as in the previous chapter. For the drivers with a `Work` profile, however, the `arrival` and `departure` times were interchanged. Therefore, those with a `Home` parking profile use the car park when they are at home, and those with a `Work` profile use the car park when they are at work. Similarly, the parking duration includes the time of `arrival` and all the hours until one hour before the `departure` time. A minimum of 3 hours and maximum of 23 hours are defined in this model. This allows the drivers to be plugged in from 2 to 22 hours at most. Moreover, a random variability of -1 to +1 hour is introduced in their daily driving schedules, where possible. For drivers who have one of the driving times at 0 and/or 23 hours, this variability is adjusted accordingly.

Techno-economic parameters

Table 7.11 shows the techno-economic input parameters used in the model. They are based on the calculations and sources used in (Oldenbroek et al., 2017) for the *Mid-century scenario* (2050).

Table 7.11: Techno-economic input parameters. Source: (Oldenbroek et al., 2017)

Variable	**Value**
HHV	39.41 kWh/kg
Electrolyzer efficiency (η_{el})	82%
FCEV efficiency (η_{FC})	61%
FCEV fuel consumption	0.006024 kg hydrogen/km
Water input	8.92 kg water/kg hydrogen

Table 7.12 and 7.13 are used to calculate the total costs of the system. The annual hydrogen production is estimated using the calculated market prices, the calculated annual PV generation and the `maxBuyPrice`. Using a `maxBuyPrice` of 15 €/MWh for all energy scenarios, we calculate the corresponding system levelized cost of hydrogen (SLCoH) and the resulting cost of V2G (Table 7.14). For the total cost calculations (see section 7.3.3), a weighted average cost of capital (WACC) of 3% was used (Oldenbroek et al., 2017).

Table 7.12: Technical component properties and costs. Source: (Oldenbroek et al., 2017)

Component	**Capital Costs**	**Lifetime (years)**	**O&M Costs, %**
Electrolyzer	250 €/kg	30	3.20
Compressor	3,650 €/kg/h	10	2
Hydrogen Storage	575 €/kg	30	1
Dispenser	72,890 €/unit	10	1.1
Rainwater collector	21,030 €/m^3/day	50	0.33
Reverse Osmosis	1.2 €/L/day	25	4.8
PV system	440 €/kWp	30	4.7
Discharger poles	3,200 €/4-unit	15	5
FCEV	21.7 €/kW	8,000 hours	5

Table 7.13: Technical component capacity or units

Component	Capacity or units
Electrolyzer	1000 kW
Compressor	1
Hydrogen Storage	2200 kg
Dispenser	1 units
Rainwater collector	1 units
Reverse Osmosis	1 units
PV system	500 kW
Discharger poles	50 units

Table 7.15: Model assumptions

	Model assumptions
1	The aggregator only participates in the day-ahead market.
2	The aggregator only uses the electrolyzer-hydrogen system and FCEVs in the car park to buy and sell electricity.
3	Hydrogen can be imported and exported at the same price to meet the CPPP system's needs.
4	Drivers have a constant daily driving distance throughout the simulation.
5	Once in the car park, cars do not leave until the scheduled departure time.
6	Drivers only refill their hydrogen tanks in the car park.
8	The aggregator's costs for participating in the market are not considered.
9	Given the number of uncertainties in the availability and hydrogen level of each vehicle throughout the day, the aggregator does not optimize the buy/sell decisions based on the hydrogen storage balance or the aggregated drivers' availability.

Table 7.14: Estimated SLCoH and cost of V2G

Energy scenario	SLCoH, €/kg	Cost of V2G, €/MWh
80SWLC	1.47	62.50
80SWMC	1.47	62.50
80SWHC	1.47	62.50

7.3.5. Model assumptions

The assumptions used in the model are listed in Table 7.15.

7.3.6. Model verification

To confirm whether the model and sub-models were implemented correctly, we carried out the verification - following the steps indicated in (K. H. Van Dam et al., 2013). An overview of the tests carried is shown in Table 7.16. In the Appendix B we explain the tests 2 through 4 in more detail, with the corresponding figures and tables.

As indicated in the table, recording and tracking behavior was done at an earlier

Table 7.16: Overview of verification tests

	Test	Description
1	Recording and tracking behavior	`print` function to communicate changes in agent states.
2	Single-agent testing	1 Driver agent. Driver methods: `makeContract`, `drive`, `refill`, `plugin`.
3	Interaction testing in a minimal model	1 aggregator, 2 Driver agents, Day-Ahead market agent. Aggregator methods: `plan`,`operate`,`V2Goperation`, `settle`, `evaluate`. Driver methods:`adjustStrategy`.
4	Multi-agent testing	1 Microgrid operator, 500 Drivers: all previous methods.
5	Variability testing	50 repetitions carried out.

stage by using the `print` function. This allowed the observation of the agents' internal processes. Also, before the final simulation experiment a variability testing was done by carrying out 50 repetitions. Moreover, after the base case simulation more repetitions were done with the sensitivity runs. After some necessary corrections, the expected outcomes were obtained and therefore the model is considered to be verified.

7.3.7. Model validation

Following the model verification the model validation is carried out to evaluate whether the model built is appropriate for addressing the modeling question. According to K. H. Van Dam et al. (2013), there are several methods to validate a model: through historic replay, expert consultation - also known as face validation, literature validation and model replication. When a model is built to explore mechanisms and phenomena that cannot be observed in the real world, expert validation becomes a useful approach to validate the model. As the model presented in this chapter explores the implementation of vehicle-to-grid contracts with fuel cell vehicles and new prosumer behavior of drivers, it is not possible to validate the results using historical or empirical data.

Like the model presented in Chapter 6, the assumptions and mechanisms of the model presented in this chapter, as well as the results, were presented to an expert in the field. At different stages of the model development, the concepts were presented in a conference paper and discussed with peers and refined accordingly. Therefore, the model is deemed appropriate to answer the research question of this chapter.

Therefore, we carried out an expert consultation to discuss the assumptions and model mechanisms. The aspects discussed in the validation can be found in Appendix B.

7.4. Simulation and results

In this chapter we present the results of the simulation experiments. First, we introduce the initialization of the six scenarios that were run for 8760 steps corresponding to one year, with fifty repetitions. Then, we present the results, starting with the hydrogen balance, followed by the amount of total aggregated V2G supplied in each scenario. The aggregator and drivers' profits are also discussed. To explore the relationship between driver characteristics and their profit level, we perform a Latent Class Analysis. Some input parameters that have an influence on the drivers' profits are explored in the sensitivity analysis. Finally, the overall findings are discussed, followed by the conclusions.

7.4.1. Simulation Experiments

Six scenarios are defined for the simulation experiments, as presented in Table 7.17. Each one consists of an energy scenario and a dispatch rule, which is the decision rule used by the aggregator to start-up vehicles when supplying V2G. Thus, it is a decision rule of the aggregator that can affect drivers' opportunities to provide V2G. With the *SU* dispatch rule, the aggregator starts up vehicles following an ascending order of total `startUps`. With this rule, cars that have been used fewer times are started up first (See Chapters 4 and 6). When the *fuel* dispatch rule is used, the aggregator starts up vehicles based on descending `fuelAvailability` order. In this case, cars that have a higher fuel availability are used first.

In every simulation, the model, the aggregator and the driver agents are created with the values in Table 7.18, Table 7.19 and Table 7.20, respectively.

Table 7.17: Simulation experiments

Scenario	**Energy scenario**	**Dispatch rule**
80SWLC-SU	80SWLC	Start-ups ↑
80SWLC-fuel	80SWLC	Fuel availability ↓
80SWMC-SU	80SWMC	Start-ups ↑
80SWMC-fuel	80SWMC	Fuel availability ↓
80SWHC-SU	80SWHC	Start-ups ↑
80SWHC-fuel	80SWHC	Fuel availability ↓

Table 7.18: Model initialization

Variable	**Initial value**
`numAggregators`	1
`numDrivers`	500
`ticks`	8,760
`fuelSFMIN`	0.1
`fuelSFCHANGE`	0.3
`refillConditionMAX`	0.9
`refillConditionCHANGE`	0.3

7.4.2. Hydrogen Balance

Table 7.21 shows the balance of hydrogen in the six scenarios. The amount of hydrogen produced is only dependent on the market price and the aggregator's `maxBuyPrice`. Therefore, it is the same for each energy scenario and is not influenced by the dispatch rule or the behavior of drivers. In all scenarios, the `maxBuyPrice` is 0 €/MWh and the amount of hydrogen produced is the same.

The results show that in the first and second energy scenarios (80SWLC and 80SWMC) the CPPP is a net exporter, while in the last it is a net importer of hydrogen.

Table 7.19: Aggregator initialization

Variable	**Initial value**
Aggregator	
maxBuyPrice	0 €/MWh
minSellPrice	average minPrice drivers
maxSellVol	800 kW
dischargerPoles	40
dischargers	4 * dischargerPoles
PoP	10 kW
Electrolyzer-Hydrogen System	
elecCapacity	1,000 kW
HSlevel	(random uniform: 0.5 to 1) * HSmax
HSmax	2,200 kg
HSmin	0.1 * HSmax
PV system	
PVcapacity	500 kW

Table 7.20: Driver agents and contract initialization

Variable	**Initial value**
Driver	
pProfile	random: "Work" or "Home"
hydrogenLevel	random uniform: 2.3 to 5.65 kg
arrival, departure, distance	Derived from (Centraal Bureau voor de Statistiek (CBS) & Rijkswaterstaat (RWS), 2015)
fuelSF	1.5
refillCondition	0.10
fuelMax	5.64 kg
hydrogenPrice	SLCoH (Table 7.14)
V2G contract	
contrCost	TCdis / numDrivers * 0.5 = 17.12 €
evalPeriod	30 days
guarFuel	minFuelDriving * fuelSF
driverMargin	Eq. 7.1
minPrice	1000 * hydrogenPrice / (FCefficiency * HHV)

We assumed that hydrogen is imported and exported at the same price, and therefore did not account for possible price differences that could affect the aggregator's business case.

The initial hydrogen price used in the model is the estimated annual SLCoH of each energy scenario (Table 7.14). This price is updated after every evaluation period (30 days), by calculating the SLCoH of the cumulative fraction of the year. The price changes throughout the year, based on the amount of hydrogen produced every month, as shown in Fig. 7.10. The same pattern is seen in all three energy scenarios, since the amount of hydrogen produced is the same.

Table 7.21: Hydrogen balance in tons: mean, standard deviation

Scenario	Produced	Refilled		Imported		Exported	
		mean	s.d.	mean	s.d.	mean	s.d.
80SWLC-SU	97.73	76.33	1.93	18.45	0.91	39.29	1.56
80SWLC-fuel	97.73	76.31	1.81	17.84	1.03	38.75	1.62
80SWMC-SU	97.73	91.21	1.47	25.47	0.42	31.40	1.37
80SWMC-fuel	97.73	90.79	1.58	25.37	0.29	31.66	1.58
80SWHC-SU	97.73	124.23	1.87	50.47	1.52	23.35	1.17
80SWHC-fuel	97.73	123.87	1.84	50.20	1.47	23.43	1.11

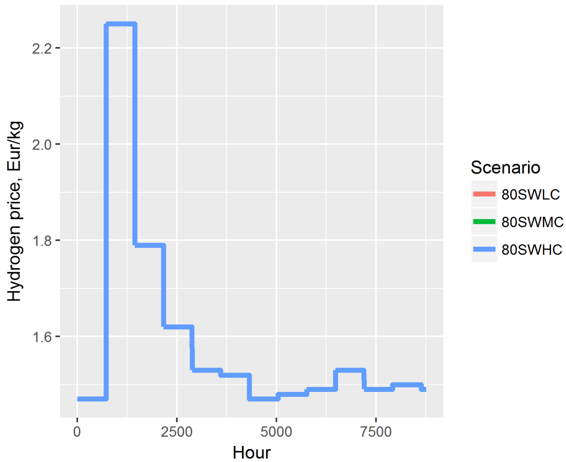


Figure 7.10: Hydrogen price throughout the year, equal for all three energy scenarios

7.4.3. Vehicle-to-grid supply in the market

The amount of V2G sold in the day-ahead market in the six scenarios is shown in Table 7.22. The average volume of V2G supplied is higher in scenarios with higher carbon price, as average electricity prices increase, although the difference is less significant between the 80SWMC and 80SWHC scenarios. At times, the amount of V2G sold cannot be delivered. When there are not enough vehicles the amount of V2G dispatched is adjusted down to the nearest 100 kWh, following market rules. The total amount of V2G planned and not delivered is highest in the 80SWMC-SU scenario. Nevertheless, this only amounts to 0.9 and 1.4% through all scenarios.

As mentioned in the previous section, the price of hydrogen is updated after every evaluation period. This influences the drivers' contractual minimum price, as it is updated once they refill hydrogen with a different price. Once the minimum price starts being updated across the vehicles, there may be hours in which V2G is scheduled but is not profitable for all the available vehicles. Since the aggregator always bids a fixed volume in the day-ahead market, the actual V2G delivered is adjusted whenever there is a shortage of dispatchable vehicles. This occurs in the model because we do not take into account the uncertainties regarding the timing at which vehicles change their minimum

Table 7.22: Vehicle-to-grid supplied, and market prices

Scenario	**V2G supplied, MWh**		**Not supplied, MWh**		**Min. sell price, €/MWh**	**Market price €/MWh**
	mean	s.d.	mean	s.d.	mean	mean
80SWLC-SU	574.45	1.51	2.83	0.58	67.89	25.14
80SWLC-fuel	570.18	1.60	5.40	0.69	68.06	25.14
80SWMC-SU	922.52	1.41	6.71	0.85	67.93	29.42
80SWMC-fuel	919.81	1.88	7.25	1.10	68.10	29.42
80SWHC-SU	1,723.44	2.93	26.15	1.97	68.05	34.60
80SWHC-fuel	1,717.08	3.31	23.10	1.95	68.18	34.60

price in the aggregator's decision-making. This timing depends not only on their driving schedule (fixed daily hydrogen consumption) but also on the amount of V2G supplied the previous day and previous hours, which will influence their refilling actions. In order to avoid differences between the scheduled and dispatched V2G, the aggregator would have to predict the states of every vehicle throughout the day. To do so, he would have to know the hourly **level of hydrogen** and the **minimum price** of the plugged in vehicles. This prediction should also take into account the uncertainty in driving time for each vehicle, which can vary in +- 1 hour in the model. Moreover, costs related to the adjusted amount of V2G are not taken into account. We could expect, however, that the aggregator would have to purchase flexible generation from other balance responsible parties or use other resources he owns. These differences could be adjusted in the intraday market, which is not addressed in the current model.

The average `minSellPrice` calculated by the aggregator throughout the year is shown in Fig. 7.11. This follows the same trend as the hydrogen price (Fig.7.10), and is smoothed out following the drivers' refilling behavior.

7.4.4. Aggregator profitability

The aggregator's profit from V2G clearly increases with higher volume of V2G supplied. Within the same energy scenario, the profit is usually higher in the *SU* dispatch rule. This is because with the *fuel* dispatch rule, the vehicles used first are those with highest `fuelAvailability` and therefore highest `driverMargin`, increasing the costs for the aggregator. As shown in Table 7.23 the profit from the operations of the hydrogen system also increase with increasing volume of V2G supplied, although it is less significant.

7.4.5. Driver profitability

Table 7.24 shows the mean and standard deviation of net profit for drivers with Home and Work profiles. In almost every scenario, the average profit of the Home drivers is higher than that of the Work profile drivers. In the Low Carbon scenarios, the average is profit is negative, while in the Medium and High Carbon scenarios, the average profit ranges between 12 and 53 €/year. As Fig. 7.12 shows, there is a high variability in drivers' net profit, especially in the *fuel* scenarios. Although the contract parameter `minPrice` ensures that drivers do not have operational losses in V2G supply, the annual contracting

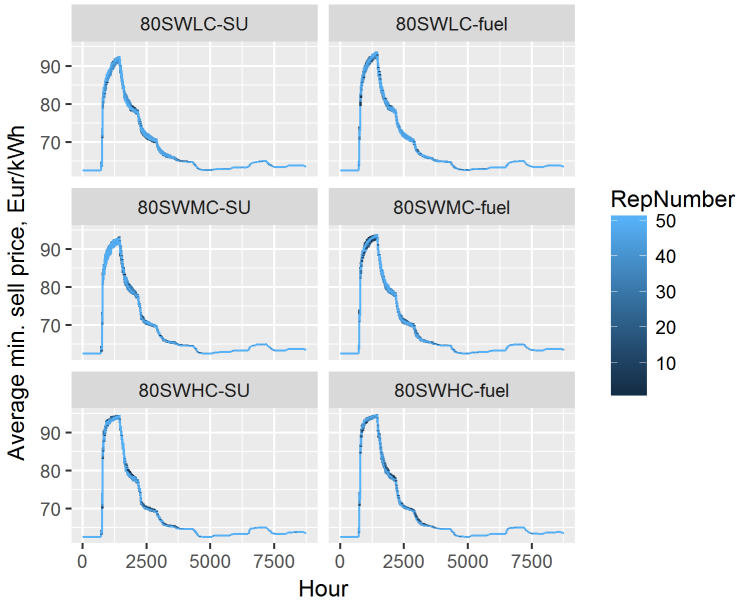


Figure 7.11: Average minimum selling price of V2G electricity throughout the year

Table 7.23: Average aggregator net profits

Scenario	**Profit V2G, k€**		**Profit Hydrogen System, k€**	
	mean	s.d.	mean	s.d.
80SWLC-SU	114.74	1.10	10.77	0.48
80SWLC-fuel	101.13	0.72	10.91	0.45
80SWMC-SU	243.15	1.89	10.90	0.75
80SWMC-fuel	216.19	1.18	10.12	0.46
80SWHC-SU	439.51	2.87	11.53	0.49
80SWHC-fuel	397.25	1.81	11.23	0.64

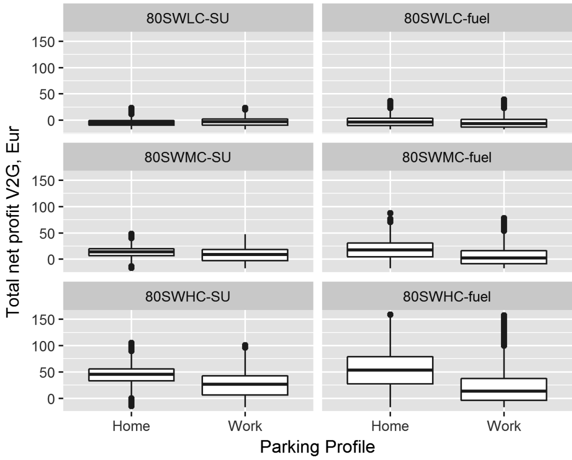


Figure 7.12: Driver profits for each parking profile

fee is considered in the net profit calculation. As a result, some users that have very low V2G revenues have a negative net revenue at the end of the year.

Table 7.24: Average driver profit by parking profile

Scenario	Net profit V2G, €			
	Home profile		Work profile	
	mean	s.d.	mean	s.d.
80SWLC-SU	-4.97	0.35	-3.13	0.38
80SWLC-fuel	-2.83	0.57	-4.36	0.56
80SWMC-SU	12.84	0.65	8.34	0.56
80SWMC-fuel	18.04	1.45	5.69	1.10
80SWHC-SU	43.05	1.76	25.78	1.20
80SWHC-fuel	53.46	3.27	19.98	1.82

Table 7.25 shows the average start-ups and V2G supplied, per vehicle. The average number of start-ups ranges from around 3 (80SWLC) to 7 (80SWMC-SU) times per month. In terms of the volume supplied, every vehicle supplied on average 31 to 48 kWh for every start-up.

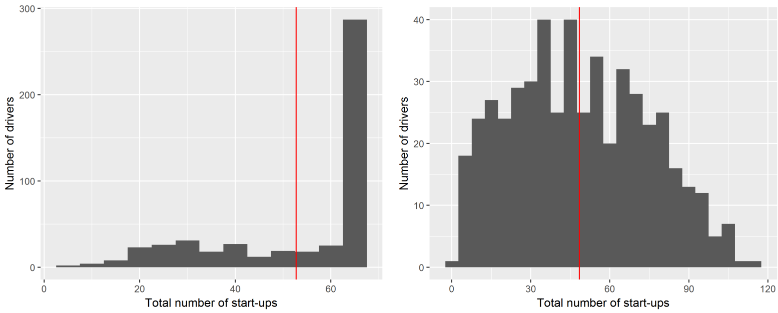
Figure 7.13 and Figure 7.14 show the distribution of total start-ups and total volume of V2G supplied in one of the 50 repetitions, for the 80SWMC-SU and 80SWMC-fuel scenarios. In the 80SWMC-SU scenario, there are more drivers with the similar number of start-ups, whereas in the 80SWMC-fuel scenario the results are more spread out. The same difference is seen in the volume supplied, between the *SU* and *fuel* scenarios.

Adaptive behavior

As explained in section 7.3.3, driver agents can change their characteristics to try to increase profits in two ways. They can either by decrease the *fuel safety factor* and

Table 7.25: Average driver start-ups and total volume supplied

Scenario	Start-ups		Average volume supplied, kWh	
	mean	s.d.	mean	s.d.
80SWLC-SU	37.13	0.45	1,148.91	2.99
80SWLC-fuel	33.98	0.30	1,140.36	3.16
80SWMC-SU	53.44	0.63	1,845.04	2.80
80SWMC-fuel	48.02	0.45	1,839.62	3.72
80SWHC-SU	82.32	1.19	3,446.87	5.80
80SWHC-fuel	71.97	0.79	3,434.16	6.54



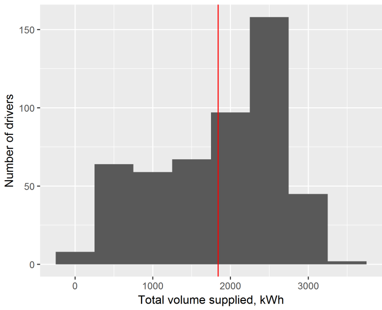
(a) 80SWMC-SU scenario (b) 80SWMC-fuel scenario

Figure 7.13: Distribution of total start-ups among drivers in a single simulation run

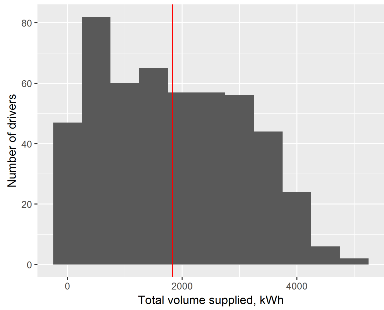
change the contract parameter `guarFuel`, or increase the `refillCondition` to refill more often when arriving at the car park. Fig. 7.15a shows that agents with the highest `refillCondition` at the end of the simulation are in the lower range of profits. Agents with the lowest refill condition are those that do not need to change their refilling strategy because they already have a higher profit level than the average. The same happens with the fuel safety factor, as shown in Fig. 7.15b. Drivers that have reduced the `fuelSF` the most at the end of the simulation also have generally the lowest profit levels. The results indicate that while changing the behavior and preferences may help some drivers increase their profits, their initial properties may limit the chances of some drivers to supply vehicle-to-grid power.

Drivers' initial properties vs. net profit

The causal loop diagram in Fig. 7.4 visualizes how initial properties can influence drivers' chances to sell V2G power. To analyze the extent to which each initial property affects their profit potential, we explore the link between three initial characteristics (parking duration, arrival time and daily driving distance) and the annual profit level. The first two are expected to influence the profits by giving drivers higher chances of being used for V2G. The latter, we assume it influences the amount of fuel available for V2G and therefore could also affect the net profit potential. Figure 7.16 shows that there is indeed a relationship between some initial characteristics of the drivers and the annual net profit level.

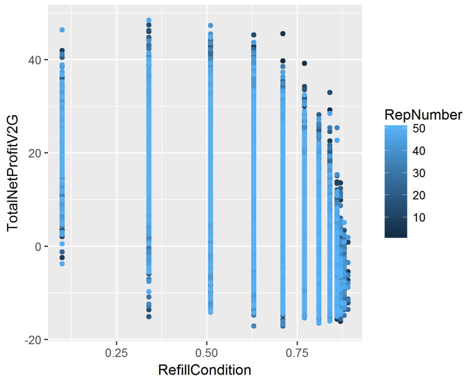


(a) 80SWMC-SU scenario

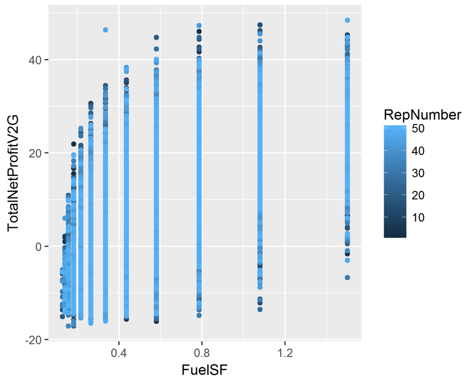


(b) 80SWMC-fuel scenario

Figure 7.14: Distribution of total volume supplied among drivers in a single simulation run



(a) Refill condition vs total net profit

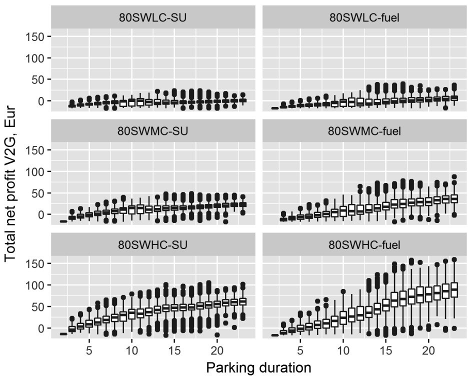


(b) Fuel safety factor vs total net profit

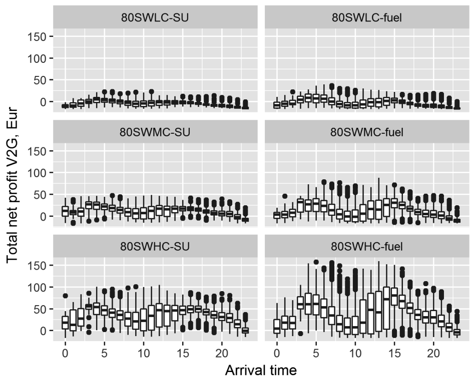
Figure 7.15: Adaptation vs total net profit, 80SWMC-SU scenario

Figure 7.16a shows the relationship between parking duration and the drivers' net profit, using the results from all 50 repetitions. Drivers with the highest net profit have a generally a higher parking duration. As expected, the longer the parking duration, the higher the chances are that the vehicle will be used for V2G. This relationship is more pronounced in the *fuel* dispatch scenarios, and with higher carbon prices. It is accompanied, however, by an increased variability. It is important to point out that some agents with high parking duration still have negative a net profit. Even when a car has a high parking duration, the time of arrival could be more important, given that the number of dischargers in the parking is limited.

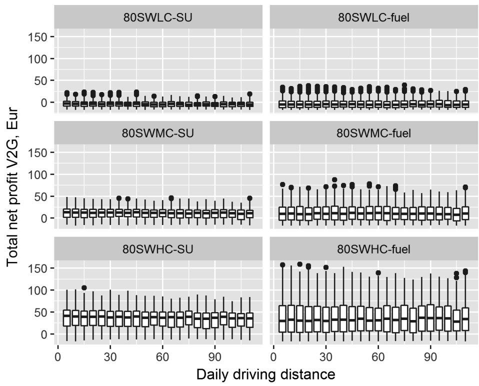
As shown in Fig. 7.16b the arrival time also has a notable effect on the net profit, which fluctuates throughout the day. There are some arrival times that seem to lead to higher average profits. This pattern is also more evident in the *fuel* dispatch scenarios and with increasing carbon prices. Higher average profit levels are seen around early morning hours (5 hours) and again in the afternoon, around 15 hours. Finally, the daily driving distance, which is used to define the contractual guaranteed fuel level, is also



(a) Parking duration vs total net profit, all drivers



(b) Arrival time vs total net profit, all drivers



(c) Distance vs total net profit, all drivers

Figure 7.16: Driver characteristics vs total net profit

analyzed. Fig. 7.16c shows distance does not have any effect on the net profit. The average profit at every driving distance group seems to remain rather constant across all distances. Again, variability increases in the *fuel* dispatch scenarios and with increasing carbon price.

Latent class analysis

Drivers' initial characteristics such as the parking duration and arrival time seem to be indicators of V2G profit potential. In addition, Fig. 7.12 also showed that the Home parking profile leads to higher average profits. Based on the figures above we further analyze the relationship between these initial characteristics and drivers' profit potential.

Using LatentGOLD® we perform a Latent Class Analysis (LCA) (Kroesen, Molin, & van Wee, 2011; Magidson & Vermunt, 2004) on the 80SWHC scenarios. Thus, we cluster agents into different groups with shared characteristics to determine the probability of an agent being in a high profit level group based on its initial characteristics.

Before fitting the results to latent class models, the nominal variables to be analyzed are re-coded into ordinal ones. For instance, in the parking duration, we divide the values into three levels: 3 to 9 hours, 10 to 16 hours, and 17 to 23 hours. For both the 80SWHC-SU and 80SWHC-fuel scenarios we use the parking profile, arrival time and parking duration as indicators and the total net profit as a covariate.

80SWHC-SU Scenario The drivers' final results are first fitted to models with 1 to 8 classes or clusters, initially only using the indicators: parking profile, arrival time, parking duration. Table 7.26 shows the results for each cluster size model. With the lowest Bayesian Information Criterion (BIC) value, the 5-cluster model appears to be optimal for the 80SWHC-SU scenario. Thus, we estimate a 5-cluster model, this time adding the net profit as a covariate.

Table 7.26: Results of latent class models using results of the 80SWHC-SU scenario

No. clusters	LL	BIC(LL)	Npar	L^2	df	p-value	Class.Err.
1	-69,472.76	138,996.15	5.00	37,562.03	12.00	6.3e-8138	-
2	-53,909.42	107,909.98	9.00	6,435.35	8.00	2.1e-1388	-
3	-51,677.27	103,486.19	13.00	1,971.05	4.00	9.7e-426	0.05
4	-50,773.90	101,719.95	17.00	164.31	-	.	0.09
5	-50,693.23	101,599.12	21.00	2.98	-4.00	.	0.07
6	-50,693.23	101,639.63	25.00	2.98	-8.00	.	0.20
7	-50,693.19	101,680.06	29.00	2.90	-12.00	.	0.15
8	-50,693.22	101,720.62	33.00	2.95	-16.00	.	0.18

Table7.27 shows the probabilities in the 5-cluster model. First, the cluster size indicates a drivers' probability of belonging to a certain cluster. For each indicator level, we can observe the probability of a driver belonging to a class based on the indicator value. For instance, for agents with an arrival time from 8 to 15, there is a probability of 0.481 of belonging to Cluster 1. Thus, the probabilities add up to 1 horizontally.

While the probabilities indicate the distribution of membership within each indicator level (horizontally), it does not indicate the distribution of every indicator level within each class (vertically). Additional results from the model show the distribution of probabilities of each indicator level within every cluster, as depicted in Fig. 7.17. There is a higher probability of being in a high profit level in Cluster 4, but it accounts only for 18.7% of the drivers. Drivers in this cluster have a Home profile, arrive mostly between 8 and 15 hours and stay parked for 17 to 23 hours a day. On the other hand, drivers with a Home profile that arrive between 16:00 and 23:00 and stay parked for up to 16 hours have only the lowest profit level, as seen in Cluster 5.

In Cluster 3, agents have a Work profile and similar chances of having an arrival time between 0 to 7 and 8 and 15. The parking duration is mostly from 10 to 16 hours, and the profit levels are mostly between 23.50 and 64.49 €per year. The cluster with lowest profit potential is Cluster 1, in which driver agents have a Work profile, with arrival times of mostly 8 to 15 hours, and short duration times. Finally, Home profile drivers with arrival times between 16 and 23 that stay mostly for 10 to 16 hours have fair profit levels.

In general, clusters with more chances of high profit levels have a high proportion of early arrival times (0 to 7 or 8 to 15 hours) and medium to long parking durations. On

Table 7.27: Probabilities of the 5-cluster model, 80SWHC-SU scenario

N = 25,000	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
luster size	0.293	0.2483	0.2049	0.1869	0.0669
Indicators					
`pProfile`					
Home	0	0.4945	0	0.3723	0.1332
Work	0.5884	0	0.4116	0	0
`arrival`, time					
0 to 7	0.2749	0	0.7195	0.0056	0
8 to 15	0.493	0.0229	0.1904	0.2938	0
16 to 23	0.0322	0.6593	0.0002	0.1224	0.1858
`parkingDuration`, hours					
3 to 9	0.8207	0.0025	0.0918	0	0.085
10 to 16	0.0023	0.4684	0.4141	0.0251	0.0902
17 to 23	0	0.2416	0.0196	0.7383	0.0005
Covariates					
`totalNetProfitV2G`, €					
-17.50 to 23.49	0.7438	0.0303	0.0061	0.0003	0.2195
23.50 to 64.49	0.1069	0.3809	0.2957	0.2165	0
64.50 to 105.49	0	0.0281	0.2603	0.7115	0

the other hand, clusters with the lowest profit levels have either short parking durations or arrival times after 16 hours. This is in line with the previous analyses, which show that drivers have on average higher profits if they: 1) arrive around 5 am and 3 pm, 2) have high parking durations, and 3) have a Home parking profile. This analysis also shows that medium to long parking durations combined with early arrival times can be more profitable than, for example, short to medium parking durations combined with late arrival times.

80SWMC-fuel Scenario Following the same steps, we carry out the latent class analysis with the results from the 80SWHC-fuel scenario, using also the parking profile in this case. Table 7.28 show the results for different models, with 1 to 8 classes. The BIC values indicate that also in this case the 5-cluster model is optimal for the results.

Table 7.28: Results of latent class models using results of the 80SWHC-fuel scenario

No. clusters	**LL**	**BIC(LL)**	**Npar**	**L^2**	**df**	**p-value**	**Class.Err.**
1	-69,617.00	139,284.63	5.00	37,039.90	12.00	1.4e-8024	-
2	-54,329.30	108,749.74	9.00	6,464.49	8.00	1.0e-1394	-
3	-52,161.82	104,455.29	13.00	2,129.54	4.00	4.0e-460	0.05
4	-51,195.79	102,563.73	17.00	197.47	-	.	0.09
5	-51,098.54	102,409.74	21.00	2.98	-4.00	.	0.07
6	-51,110.38	102,473.92	25.00	26.65	-8.00	.	0.18
7	-51,098.49	102,490.65	29.00	2.87	-12.00	.	0.18
8	-51,098.30	102,530.79	33.00	2.50	-16.00	.	0.18

With the profile results, we visualize the distribution of probabilities of each indicator level within every cluster in Fig. 7.18. Most of the high level profits correspond to drivers in Cluster 3: drivers with a Home profile who arrive mostly between 8 and 15 and stay

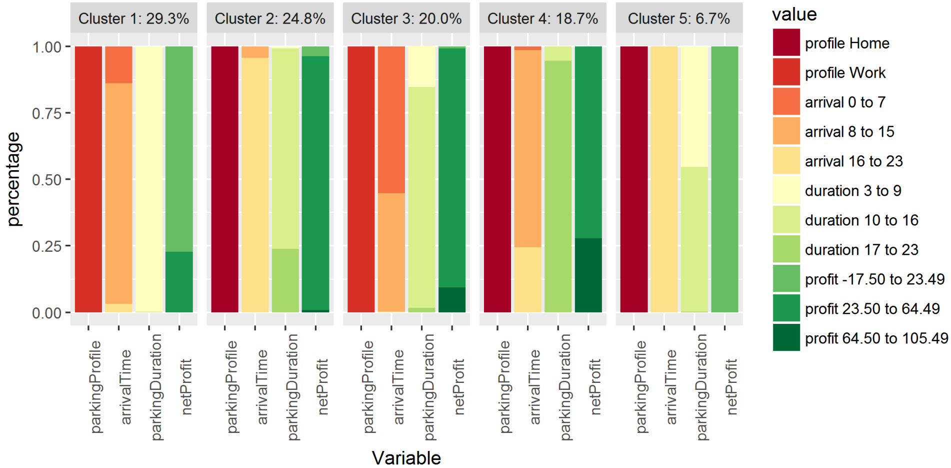


Figure 7.17: Visualization of clusters from the latent class analysis of driver results in the 80SWHC-SU scenario

Table 7.29: Probabilities of the 5-class model, 80SWHC-fuel scenario

N = 25,000 **Cluster size**	**Cluster 1** 0.3942	**Cluster 2** 0.1766	**Cluster 3** 0.1606	**Cluster 4** 0.1572	**Cluster 5** 0.1114
Indicators					
`parkingProfile`					
Home	0.0001	0.3572	0.3248	0.318	0
Work	0.7796	0	0	0	0.2204
`arrival`, hours					
0 to 7	0.4896	0	0.0054	0	0.505
8 to 15	0.6204	0.0359	0.2841	0	0.0596
16 to 23	0.0373	0.453	0.0621	0.4475	0
`parkingDuration`, hours					
3 to 9	0.9059	0.0001	0	0.085	0.009
10 to 16	0.1832	0.2311	0.0199	0.3123	0.2534
17 to 23	0.0001	0.343	0.6294	0.0036	0.0238
Covariates					
`totalNetProfitV2G`, €					
-17.50 to 41.49	0.6725	0.0491	0.0008	0.2699	0.0076
41.50 to 100.49	0.0072	0.4074	0.3123	0.0001	0.2731
100.50 to 159.49	0	0.0116	0.8414	0	0.147

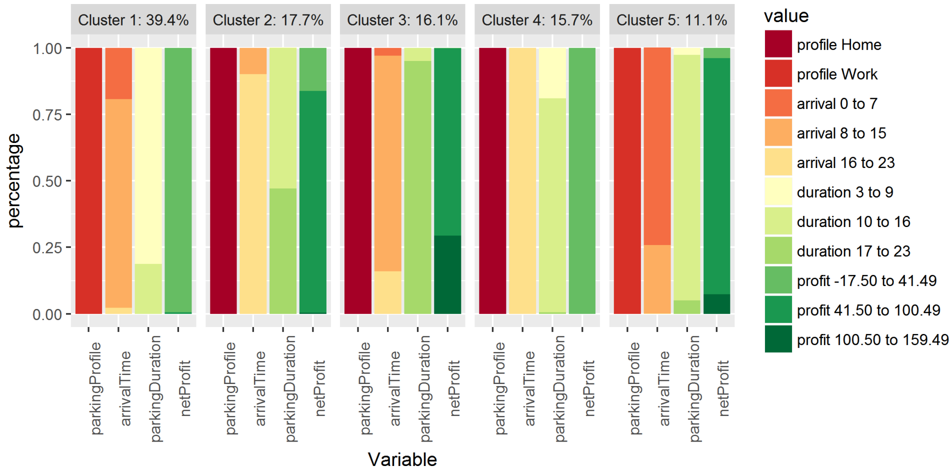


Figure 7.18: Visualization of clusters from the latent class analysis of driver results in the 80SWHC-fuel scenario

parked throughout the day, for 17 to 23 hours. The lowest profit levels are concentrated again in Cluster 1: drivers with a Work profile who arrive anytime before 15h and stay for 9 hours or less.For drivers with a Work profile, those arriving mostly before 8 AM and staying for 10 to 16 hours have higher chances of profiting from V2G, as shown in Cluster 4.

The results of the two latent class analyses demonstrate that even with more variability in the profit potential, the characteristics of high and low earning groups are similar. While the cluster sizes are different, the combinations between parking profile, arrival time, parking duration and profit potential are fairly comparable.

7.4.6. Sensitivity analysis

The goal of this model is to explore how contract parameters and V2G operating strategies influence the profit potential of drivers and the aggregator, in electricity systems in transition. To do this we modeled future electricity systems with high solar and wind penetration and a range of carbon allowance prices. Furthermore, some decisions were made regarding the system sizing and the operations of the aggregator, all of which can affect the profit of all actors. There are several aspects that may affect the net profit of drivers in the supply of V2G. Some aspects are external to the drivers like the number of discharger poles installed by the aggregator, or internal, like the drivers' initial characteristics or their adaptive behavior. Both external and internal aspects can affect the drivers' opportunities to participate or the level of profit they can realize in the market.

In this section, we explore the effect of five aspects that may influence the aggregator and drivers' results in different ways; the first two corresponding to the aggregator, and the last two to the drivers. The inputs used for the sensitivity analysis are shown in Table 7.30 The other input parameters are the same as in the 80SWHC-SU scenario, which has less variability in the drivers' profits. Therefore, we compare the sensitivity runs to the 80SWHC-SU scenario. First, we analyze the main outcomes in every sensitivity run, and then we present the overall results further down in Tables 7.31 and 7.32.

Table 7.30: Inputs of sensitivity analysis

	Sensitivity analysis	Inputs	Base case 80SWHC-SU
S1	Discharger poles	30 and 50	40
S2	Evaluation period	15 and 60 days	30 days
S3	Adjust strategy	No	Yes
S4	Profit margin in `minPrice`	5%	0%

S1: Number of discharger poles

The influence of arrival time on net profit suggests that the number of discharger poles affects drivers' opportunities to provide V2G. When there is a small number of dischargers, they may be fully occupied sooner. If a driver does not find free dischargers, he loses the chance to plug-in for the day and therefore to provide vehicle-to-grid power. A high number of dischargers would give more fair opportunities to all drivers. However, this would increase the contracting cost, lowering the annual net profit for all drivers. In the first sensitivity run we repeat the 80SWHC-SU scenario using 30 and 50 discharger poles (120 and 200 plug-in points).

As Figure 7.19 shows, a higher number of discharger poles leads to lower undelivered V2G. With 30 dischargers, however, this number is tripled. This reflects the effect of the number of discharger poles on the number of available and dispatchable vehicles. Plugged in vehicles are considered available when they have enough fuel for V2G and dispatchable when the minimum price is below the market price. With fewer possibilities to plug-in, the number of available, and especially dispatchable vehicles is reduced. While there may be drivers with lower minimum prices, if they have not been able to plug-in, the aggregator cannot use their vehicles.

For drivers, an increase in discharger poles means a decrease in the average profit, as depicted in Fig. 7.20a, due to the increased contracting costs. The average revenues remain roughly the same (Fig. 7.20b), albeit with less variability when the number of dischargers increases. Finally, Fig. 7.21 shows the influence of discharger poles on the profit level at different arrival times. With only 30 dischargers, arrival time proves to have a more evident effect on profit, especially in the early hours. With 50 dischargers, however, the chances of V2G are better distributed and so are the profits.

S2: Evaluation period

The evaluation period in the V2G contract defines the duration for which the average performance is calculated among drivers, after which they can adapt their behavior. It is also the period after which the hydrogen price is calculated. An evaluation period of 15 and 60 days is used. The results show that an increasing evaluation period leads to higher V2G profits for the aggregator. As Fig. 7.22 shows, profits from the hydrogen system are lower with a shorter and longer evaluation period.

Figure 7.23a shows the effect of increasing the evaluation period on the undelivered V2G. As discussed in Section 7.4.3, the hydrogen price update after the first evaluation

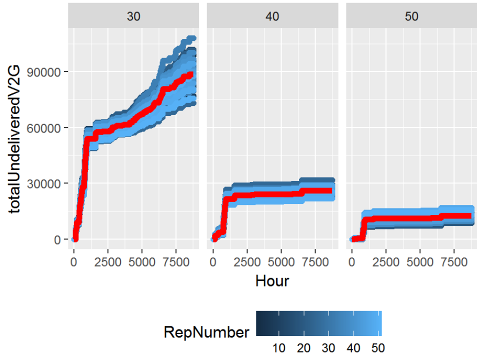
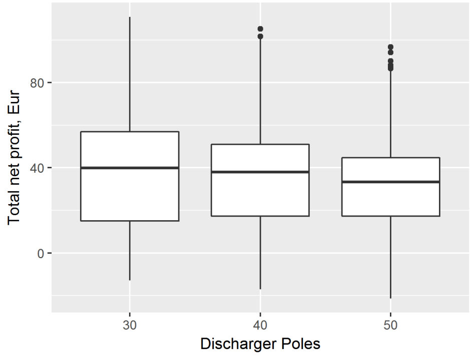
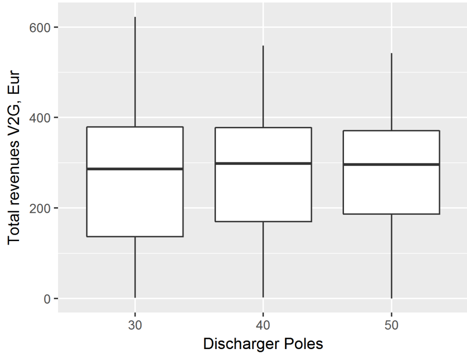


Figure 7.19: Undelivered V2G, kWh with 30, 40 and 50 discharger poles



(a) Profit from V2G



(b) Revenues from V2G

Figure 7.20: Total annual revenues and net profit for drivers in €, with 30, 40 and 50discharger poles

period has an influence on the undelivered V2G. With a period of 60 days, the average undelivered V2G is halved, but with a period of 15 days it is quite similar. The fluctuation of hydrogen price, therefore reduces the number of dispatchable vehicles shortly after the evaluation period, since the minimum price is affected.

The effect of the evaluation period on the evolution of the average minimum price used by the aggregator is shown in Fig.7.23b. With shorter evaluation periods, the minimum price is reduced after the first period, and is then almost doubled after the second period. As these changes are not considered by the aggregator when offering V2G on the day-ahead market, they are reflected as a shortage of dispatchable vehicles during a few hours after prices are updated. For drivers, the difference in average annual net profit does not vary much in between the three evaluation periods, although it is slightly higher in with 15 and 60 days.

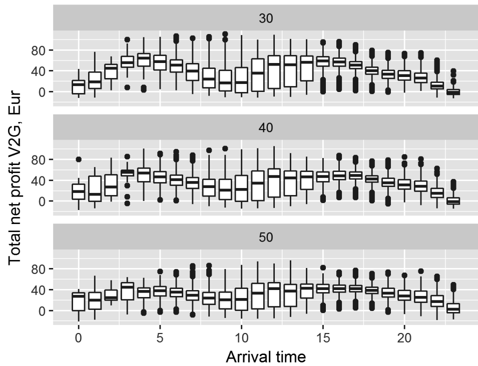
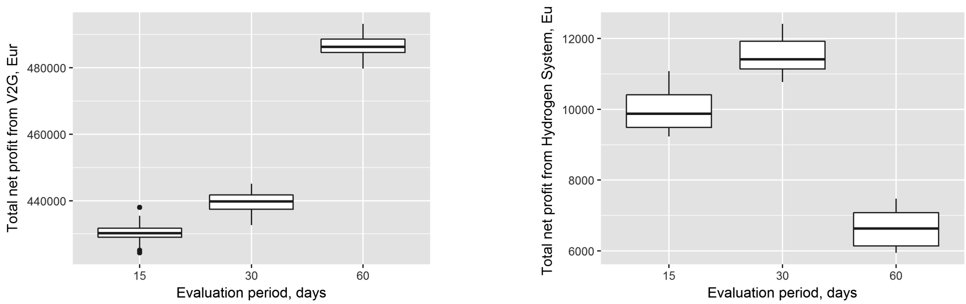


Figure 7.21: Net profit vs arrival time with 30, 40 and 50 discharger poles



(a) Profit from V2G

(b) Profit from the hydrogen storage system

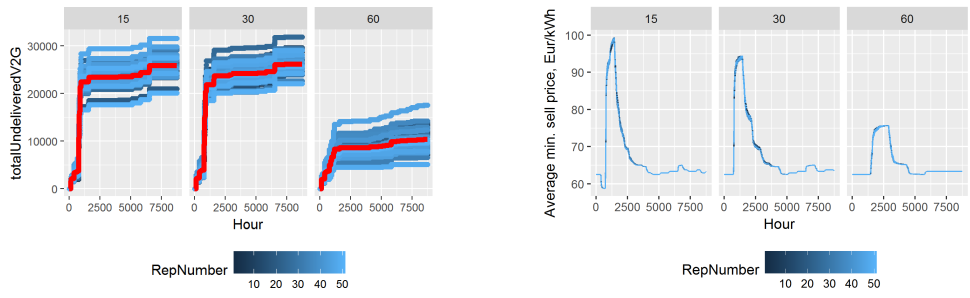
Figure 7.22: Aggregator profit with evaluation period of 15, 30 and 60 days

S3: Adaptive behavior

The adaptive behavior allows drivers to adjust the contract parameter or refilling strategy in order to increase the energy available for V2G. This can influence the total energy used for V2G as well as the driver margin for V2G. In this analysis, the adaptive behavior is removed in all agents to analyze its effect. Fig. 7.25a shows that removing this adaptive behavior benefits the aggregator. This is because drivers are not increasing the driver margin with the strategic refilling behavior. For drivers, thus, the average profit is slightly lower, as seen in Fig. 7.25b.

S4: Profit margin in `minPrice` calculation

The contract parameter `minPrice` is an additional constraint given to the aggregator for the operation of vehicles for V2G. In the base case simulation, the minimum price is calculated as the cost of providing V2G (See Table 7.20). Thus, the minimum fixed revenues are just enough to cover the costs. The driver margin defines how difference between the actual market price and the minimum price is shared between the driver and the aggregator. In this sensitivity analysis, we calculate the minimum price with a margin of 5% over the cost of V2G. Figure 7.25 shows that incorporating a profit margin



(a) Undelivered vehicle-to-grid (b) Minimum sell price used by aggregator

Figure 7.23: Undelivered V2G and minimum sell price with evaluation period of 15, 30 and 60 days

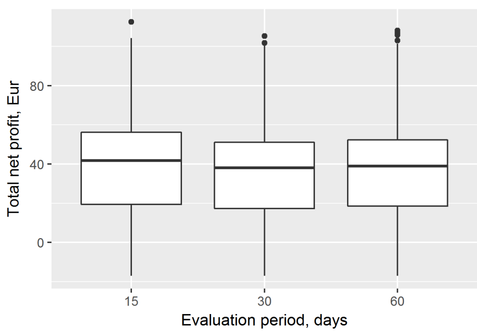
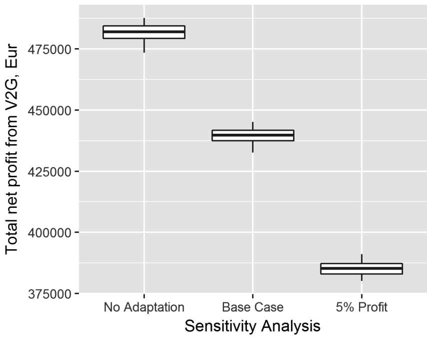
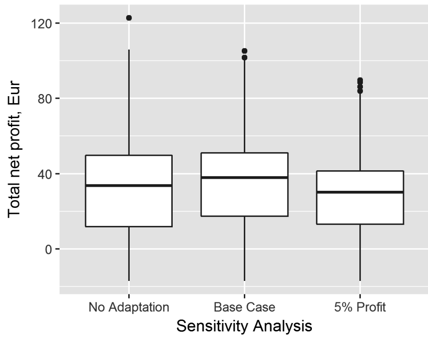


Figure 7.24: Net profit for drivers with evaluation period of 15, 30 and 60 days



(a) Net profit for Aggregator



(b) Net profit for drivers

Figure 7.25: V2G profit with *No Adaptation* and 5% profit in minimum price calculation

Table 7.31: Results of sensitivity analysis

	S1		**S2**		**S3**	**S4**
	30	50	15 days	60 days	No Adaptation	5% profit
Aggregator agent						
Refilled	122.28	**124.64**	40.54	55.68	122.44	108.99
Import	45.50	50.35	22.19	20.48	50.30	37.58
Exported	20.41	22.93	**128.04**	**130.87**	**25.03**	**25.72**
V2G supplied	1,666.26	**1,730.66**	**1,793.61**	**1,883.25**	1,681.85	1,352.98
V2G undelivered	**88.61**	12.73	25.89	10.35	**43.00**	16.21
Average min price	67.98	68.08	67.59	65.42	**68.26**	**71.37**
Net Profit HS	10.73	**11.59**	10.97	6.66	11.55	10.52
Net Profit V2G	403.56	**446.00**	430.32	**486.45**	**481.65**	385.31
Driver agents						
Drivers H profit	**46.55**	38.66	**47.23**	**44.28**	40.04	33.13
Drivers W profit	**27.51**	21.87	**28.19**	**26.89**	22.90	21.49
Start-ups	75.35	**85.80**	82.33	**93.27**	**87.34**	70.52
Volume supplied, kWh	3,332.52	**3,461.33**	**3,587.22**	**3,766.50**	3,363.70	2,705.95

in the minimum price calculation reduces profits for both the aggregator and the drivers.

Overview sensitivity analysis

Table 7.31 shows the main results in all sensitivity runs, in which results that outperform the base case run are highlighted in bold. in Table 7.32 we show the differences in percentage. The first sensitivity analysis S1 affects mostly the amount of undelivered V2G, which increases dramatically when 30 discharger poles are used. The profits for the aggregator change very little, whereas the profits for drivers change linearly by roughly +-30%. The average start-ups and volume supplied remains almost unchanged. The changes in average driver profits are attributed to the contracting cost that comes from the cost of V2G infrastructure, i.e. dischargers. Therefore, it does not affect the actual participation and revenues from V2G as much, as seen in Fig. 7.20b.

Changing the evaluation period influences the extent to which hydrogen prices and

Table 7.32: Results of sensitivity analysis as a change percentage with respect to the base case simulation of the 80SWHC-SU scenario

	S1		**S2**		**S3**	**S4**
	30	50	15 days	60 days	No Adaptation	5% profit
Aggregator agent						
Refilled	-1.6%	0.3%	-67.4%	-55.2%	-1.4%	-12.3%
Import	-9.8%	-0.2%	-56.0%	-59.4%	-0.3%	-25.5%
Exported	-12.6%	-1.8%	448.2%	460.3%	7.2%	10.1%
V2G supplied	-3.3%	0.4%	4.1%	9.3%	-2.4%	-21.5%
V2G undelivered	238.9%	-51.3%	-1.0%	-60.4%	64.4%	-38.0%
Average min price	-0.1%	0.0%	-0.7%	-3.9%	0.3%	4.9%
Net Profit HS	-6.9%	0.5%	-13.6%	-42.2%	0.2%	-8.8%
Net Profit V2G	-8.2%	1.5%	-2.1%	10.7%	9.6%	-12.3%
Driver agents						
Drivers H profit	8.1%	-10.2%	9.7%	2.9%	-7.0%	-23.1%
Drivers W profit	6.7%	-15.2%	9.4%	4.3%	-11.1%	-16.6%
Start-ups	-8.5%	4.2%	0.0%	13.3%	6.1%	-14.3%
Volume supplied, kWh	-3.3%	0.4%	4.1%	9.3%	-2.4%	-21.5%

thus minimum V2G prices fluctuate in the system. The results in S2 show that the total V2G supplied increases with a shorter and longer evaluation period. A short period seems to benefit drivers the most, who see an increase of almost 10% in their profit. For the aggregator, a longer evaluation period leads to higher profits from V2G and lower profit from the hydrogen system. When increasing the evaluation period to 60 days, there is a reduction of 60% in the undelivered V2G, which is usually affected by the update of `minPrice` after refilling with a new hydrogen price. Increasing the evaluation period reduces the average minimum sell price. Therefore, increasing the evaluation period seems to be beneficial for both the aggregator and the driver. However, fewer evaluations throughout the year provide fewer opportunities for drivers to improve their performance. It is possible that the increased drivers' profits in shorter evaluation periods are an effect of the adaptive strategies, which are used more often.

When removing the adaptive behavior, as in S3, the profits for drivers are indeed reduced. However, this behavior influences Home profile drivers more, as they see a reduction by 11%. Also, the undelivered V2G increases by 64%. The reason behind the increase could be that the adaptive behavior increases available energy for V2G - both by changing the contract parameter `guarFuel` and the `refillCondition`. With no adaptive behavior, drivers may tend to plug-in with less energy, reducing their availability. The aggregator, however, benefits from this as his annual profit increases by about 10%. The main reason could be that the contract parameter `driverMargin` is not being strategically increased by the drivers' refilling behavior.

Finally, as shown in S4, adding an additional profit margin in the `minPrice` calculation proves to be disadvantageous for all actors. For the market prices used, a mere increase of 5% in the minimum sell price reduces the profitability of V2G. By keeping the fixed revenues equal the cost of V2G, drivers can actually realize more profits by increasing their chances to sell V2G and sharing the additional income with the aggregator.

7.5. Discussion

The different scenarios explored in this chapter show that in a Car-Park Power Plant, the profit potential for drivers in the wholesale market depends on external aspects like the market prices and the operational strategy of the aggregator. Increasing market prices lead to higher average profit, and the *fuel* dispatch rule increases the average profit of drivers. However, in all cases drivers' annual net profits are highly variable, as there are some who have losses and others that earn up to 150€/year. Thus, we also looked at the internal characteristics of the drivers to understand their profit potential.

Indicators for profit potential

Some of the drivers' initial characteristics have an effect on the annual profit, namely the parking profile, parking duration and the arrival time at the car park. Through Latent Class Analysis, we explored the relationship between those characteristics and drivers' profit in both the 80SWHC-SU and 80SWHC-fuel scenarios. While a single indicator cannot ensure a certain level of profit for a driver, the clusters show that such an analysis could be used to inform drivers about expected profits, based on their characteristics. This can help reduce the uncertainties for drivers when deciding whether or not to participate in vehicle-to-grid. In practice, however, aggregators will not have perfect foresight regarding market prices and therefore may have to rely on results from previous years. An added challenge in electricity systems in transition is that increased renewable energy penetration leads to higher year-to-year fluctuations in the system's residual load. This variability can make it more difficult to estimate the profit potential.

Uncertainties for drivers

The results also show that drivers are dependent on each other to perform well. They cannot participate by themselves in the market due to the required minimum volume increments of 100kWh. Whenever the required number of vehicles is not available, the aggregator has to adjust the number of cars by a multiple of 10. Therefore, available and dispatchable vehicles are affected negatively when not enough cars are available and dispatchable. Additionally, they can only provide V2G when chosen by the aggregator. The dispatch rule and the states of all the other available vehicles influences each vehicle's chances to be operated. While they cannot ensure that their vehicle is used more often, drivers adapt their behavior to try to increase profits when they are performing worse than other drivers in the same parking profile. As shown in the sensitivity analysis, without adaptive behavior, the volume of V2G supplied decreases, on average, as well as drivers' profits.

Heterogeneity in strategies and decision-making

In the model, drivers have different initial characteristics but their strategies and the way contract parameters are calculated are the same. They react in the same way when they compare their profit level to the rest. They also adjust their behavior in the same way, although choosing a different strategy every time. Moreover, their minimum price and (initial) guaranteed fuel level is calculated in the same way. With the availability of empirical data about drivers, different types of behaviors and strategies could be introduced in the model to gain more insights about the behaviors within the social subsystem. The heterogeneity in those strategies will affect the overall performance of all drivers, since they influence each other.

Uncertainties and the aggregator model

While the results provide insights on the effect of contract parameters and operating strategies using a pool of heterogeneous drivers, there are some uncertainties that were not addressed. In the model, the aggregator's operation in the market is not optimized. We assume perfect foresight regarding prices, and allow the aggregator to buy and sell electricity regardless of the current hydrogen storage level or the future hourly availability in the car park. To improve the representation of the aggregator's operation, we suggest the use of methods that take into account uncertainties, such as robust optimization. The main uncertainty is the hourly aggregated amount of refilled hydrogen in the system. The refilling behavior of individual drivers is not predictable and depends on several factors: the current hydrogen level, the driving needs, and the hydrogen consumption for V2G throughout the next hours. However, due to the difficulty in predicting all three with the current modeling approach, the aggregator does not know beforehand which vehicles will be used for V2G the next day. Consequently, the amount of hydrogen storage cannot be predicted. Another uncertainty to be addressed is the hourly availability of FCEVs. The availability is not known beforehand due to the variability in driving schedules and the unknown level of hydrogen throughout the day (dependent on V2G operation). Currently, the amount of aggregated V2G sold is constant at 800kWh. As the results show, this volume is not always dispatched, because some vehicles might suddenly become not dispatchable. This is largely due to the updated minimum price in the contract or when successive hours with V2G use up the energy of a large part of vehicles in the car park. A different way to reduce the differences between planning and operation is for the aggregator to use the information from incoming vehicles to update the planning for the next few hours. If the intraday market is modeled as well, the aggregator could adjust the volumes in the market up to 1 hour before dispatch. Given these uncertainties and the way the aggregator was modeled, we current results underestimate the potential of FCEVs in future wholesale electricity markets. Using advanced techniques to adjust the volume and participating in short-term markets, the aggregator would be able to sell more V2G power.

Model assumptions

As presented in the model assumptions, the aggregator only participates in one market with the resources represented in this model. However, there are other resources and markets that the aggregator could exploit to profit from flexibility trading. Other markets like the intraday or balancing markets could be more attractive and profitable for the aggregator. This model only shows the day-ahead market due to the complexities and uncertainties in modeling intraday market prices in systems with high renewable generation. As mentioned earlier, allowing the aggregator to adjust its planning through the intraday market could be possible by extending this model. Without the estimation of intraday market prices, one could use the same prices as in the day-ahead market.

The flexibility that short-term markets provide would increase the supply of V2G power and therefore the profit potential for drivers and the aggregator.

Assumptions were also made about drivers, including the constant daily driving distance throughout the simulation or the assumed daily use of the car park. These assumptions increase the participation of drivers, but in practice their availability would fluctuate throughout the week, but also seasonally. Unexpected trips before the expected departure time would also make cars unavailable quite suddenly. With this in mind, aggregators should take into account the need for back-up capacity, and therefore optimize the volume of energy offered in the market. More variability could be introduced in drivers' behaviors by scheduling unpredicted trips and/or changing the driving patterns on a daily basis. This would affect the availability of vehicles for V2G, and reduce the chances to profit, given the variable electricity prices to which drivers are exposed.

Finally, the participation of other flexibility resources is not considered in the market price calculation. Other resources like residential demand-side management, large-scale batteries, or large-scale power-to-hydrogen systems would also reduce the opportunities for aggregated FCEVs to participate. The competition of different resources also needs to be explored to understand the value of FCEVs in future electricity systems. Finally, for a more complete economic analysis of an aggregator's business case, we suggest to consider additional costs such as the fee for participating in the market or possible differences hydrogen import/export prices.

Lessons for V2G implementation

The simulation experiments showed how the operational decision (dispatch rule) affect the drivers' chances for V2G participation. The sensitivity analysis showed that both investment decisions (S1) and strategic decisions (S2) made by the aggregator affect the outcome for drivers as well. Aspects like the number of discharging points in the system have a direct influence in the drivers' chances to participate. A shortage of plug-in points will benefit some drivers who always arrive earlier, but the average net profit will be lower due to reduced contracting costs. On the other hand, more discharging points can increase the opportunities for all drivers while increasing the shared costs. The V2G infrastructure costs used in this chapter are divided equally among all contracted drivers. Other ways of sharing the costs could be possible - perhaps based on the amount of plug-in hours. Decisions on the offer volume, as mentioned above, should be made taking into account all uncertainties that were not explicitly modeled in the aggregator's decision-making. The evaluation period should be used to allow more flexible contractual agreements and provide opportunities for drivers to increase participation. However, one should also consider the possibility of drivers reducing participation thanks to this flexible contract. Such changes in participation can bring more risks to the aggregator, as he is dependent on them to make a profit in the market.

As for drivers, being able to react to their performance and change their behavior can help real drivers learn from V2G participation and adapt according to their preferences. It is reasonable to consider that some drivers would be willing to adapt their behavior to benefit more from participating in V2G. Since this is profitable for the aggregator, he should investigate to what extent drivers are willing to change their behavior and under what conditions. For the system in place, the results show that drivers can benefit more if the contractual minimum price is equal to the cost of V2G. With a higher minimum price, overall participation in V2G is reduced and so are the revenues for all actors. Therefore, it is more profitable to have a lower fixed remuneration (`minPrice`) and aim to increase the variable component (`driverMargin`) by adjusting one's behavior. This aspect will also affect the aggregator's business case. Since drivers are not expected to have deep knowledge about electricity markets, the aggregator should provide recommendations for an appropriate price level for the drivers. For this, a trusting relationship between the aggregator and drivers is necessary.

Finally, in this model, the driver margin was calculated as a function of the fuel availability. The formula used is just an example of how this can be implemented. In practice, the aggregator could share the profit with the drivers using another formula. Using fuel availability, however, increases the aggregated energy for the aggregator. This is seen in S3, where the removal of drivers' adaptive behavior influences the undelivered electricity. This shows that contract parameters can be used to incentivize the extent to which drivers participate: in time or energy available. In this model, the energy availability was rewarded through the driver margin, and drivers were assumed to be willing to plug-in every day for the duration of their stay in the car park. For every type of V2G implementation considered, different aspects from V2G participation will be important to the aggregator, and therefore drivers should be rewarded differently.

7.6. Conclusions

In this chapter, we built an agent-based model of the Car-Park Power Plant and explored the profitability of the involved actors in different energy scenarios (80SWLC, 80SWMC, 80SWHC) and dispatch rules (*SU* and *fuel*) used by the aggregator. The results show how V2G becomes more profitable in energy scenarios with increasing electricity prices, as more aggregated V2G can be sold in the wholesale market. Additionally, the *fuel* dispatch rule leads to higher average profits as drivers with more fuel (and higher driver margin) are prioritized. However, given the price fluctuations and heterogeneous driving schedules, the profit potential for all drivers is not the same.

Given the heterogeneous characteristics of drivers in the model, we analyzed the relationship between their initial characteristics and their profits. The parking duration, intuitively, gives drivers a higher chance to sell vehicle-to-grid power and therefore realize more profits. However, it is not the only indicator of high profit. The limited number of plug-in points leads to some missed plug-in opportunities. Thus, other aspects such as the arrival time and parking profile also influence the profit potential. To analyze these relationships quantitatively, Latent Class Analysis was carried out on the drivers' results from the 80SWHC-SU and 80SWHC-fuel scenarios. The initial characteristics discussed above were used as indicators and the net profit as a covariate, to analyze the properties of agents belonging to different clusters. The results show that in both scenarios, drivers with a Home profile arriving mostly between 0 and 7 or 8 to 15 hours and with a parking duration of more than 17 hours are usually those with highest profits. On the other hand, drivers with a Work profile, arriving usually between 8 and 15 and staying for less than 9 hours, have the lowest profit levels.

For the aggregator, the profit is higher when the *SU* dispatch rule is used, as opposed to the drivers. When making strategic decisions, such as the number of discharger poles or the evaluation period, the aggregator has to take into account the complexities of the system. As the sensitivity analysis shows, those decisions can affect drivers' opportunities to participate and therefore their profit potential. For an aggregator to develop a successful business case, all the additional uncertainties mentioned in the previous section should be considered as well.

The model built in this chapter shows how the price-based V2G contract can be implemented and operationalized for participation in the wholesale electricity market. The parameters in the price-based contract do not only allow the aggregator to know which vehicles can be used, but also provide a flexible structure for remunerating V2G. Moreover the contract takes into account the changing remuneration needs, such as an increase in V2G cost due to changes in the hydrogen price. This is something to consider in order to ensure drivers they are properly remunerated. The contract also incentivizes drivers to increase the extent to which they participate, in this case, the energy available for V2G. Through the driver margin, calculated every day at plug-in, vehicles that have higher fuel availability are rewarded. This can be a way for the aggregator to ensure higher energy available when there is no actual commitment of plug-in time. This model allows the analysis of interactions between the different parts of the socio-technical system. More importantly, it allows to explore explicitly the effect of the contractual relationship between driver and aggregator on both actors' profitability. It also shows that certain types of drivers could potentially benefit more from participating in the day-ahead market. In this chapter, we only explored two types of dispatch rules, but they show that any other decision rule will affect the V2G operation of individual drivers and everyone's profits. Finally, the results from this model demonstrate that a techno-economic approach to studying the profitability of V2G is not enough, and that actors' behaviors and their influence have to be explored. To study energy systems in transition, a complex socio-technical systems view is needed to explore the new roles, rules, and decisions of actors that are needed to implement clean technologies provided by prosumers.

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Conclusions and Reflections

8.1. Conclusions

The main research question addressed in this thesis is: *How can prosumers' FCEVs be leveraged as flexibility resources within Car as Power Plant systems?*. In this section we discuss how this question was answered through the research sub-questions.

8.1.1. Role of institutions in vehicle-to-grid implementation

In Chapter 3, the literature review was carried out to answer the first sub-question: *"What roles do institutions play in vehicle-to-grid implementation?"*.

We classified the institutional aspects of V2G into three categories: 1) Techno-economic assessments, 2) V2G contracts, and 3) Institutional environment. Institutions in the three categories proved to provide different insights on what is needed to implement vehicle-to-grid.

Techno-economic assessments were meaningful when first analyzing the potential of vehicle-to-grid in electricity systems. In the initial studies on vehicle-to-grid, characteristics of all electric vehicles were considered to analyze their suitability in different markets, and to quantify their expected annual economic potential - considering a range of costs and revenues. Operational models on fuel cell vehicles were also used to quantify their economic potential for local energy generation, under different operational strategies and energy price scenarios. While techno-economic assessments provided insights on the potential of electric vehicles, the actors' characteristics, behaviors or preferences were not explicitly considered.

When discussing the implementation aspects of vehicle-to-grid, however, it became clear that drivers need to be engaged in order to leverage the potential of vehicles. Contracts were mentioned as a strategy to get the commitment from drivers to participate and provide their capacity, and aspects such as plug-in time or guaranteed energy level were proposed as rules for participation. Therefore, the role of contracts in vehicle-to-grid implementation is not only to secure the participation of drivers but also to manage vehicle-to-grid transactions.

Finally, the institutional environment perspective explored the barriers for implementation and the effect of policies. Qualitative analyses provided an overview of the constraints in the social system, not only in terms of the norms but also the political environment, resulting in policy advice. Operational techno-economic models, on the other hand, were used to quantify the effect of specific policies in increasing the economic potential of vehicle-to-grid. Therefore, analyzing this type of institutions helped understand how the implementation of vehicle-to-grid can be encouraged and enabled.

8.1.2. Implications of vehicle-to-grid participation

In Chapter 4, we addressed the second research sub-question: *"What are the operational implications of vehicle-to-grid participation for individual vehicles and for the system as a whole?"*.

To answer this question, we explored the operation of a Car as Power Plant microgrid, focusing on the physical system. In said system, FCEVs were used to serve the local residual demand to make for the shortage of solar electricity. We evaluated the effects of vehicle-to-grid on the system and the individual vehicles and derived conclusions on the implications of vehicle-to-grid in a CaPP microgrid at the two levels.

From the system perspective, when fuel cell electric vehicles are used as power plants, the operational performance (self-supply percentage) is constrained by the vehicles' availability. Although FCEVs are dispatchable and flexible resources, the available capacity is variable. The simulation results showed that the aggregated number of cars parked in the microgrid fluctuates throughout the day and cannot be controlled. Even with a higher number of vehicles in the system, some shortage hours were inevitable due to the low number of cars present. From a technical perspective, a car is considered available if it is 1) here, 2) not refilling, and 3) has enough fuel. Therefore, availability depends first and foremost on the driving schedules of individual vehicles. When a car is parked, an additional constraint is the amount of hydrogen. The hourly consumption of fuel in each vehicle is influenced not only by driving needs but also by V2G operation in the previous time steps. Therefore, although aggregated FCEVs can represent an important flexible resource in a system, the actual capacity depends on the vehicles' individual states and hourly operation. This underscores the importance of understanding the role of individual vehicles on the aggregated capacity for vehicle-to-grid and in turn on the system's operational performance.

From the perspective of individual vehicles, V2G operation affects their fuel level and the degradation of the fuel cell stack. In this thesis we used the number of fuel cell start-ups as an indication of the degree of degradation, and therefore operated the vehicles based on this variable. Moreover, under the assumptions that *all cars are considered available for V2G whenever they are in the microgrid*, each vehicle turned out to be available on average 50% of the day but was used only a fifth of that time. When a car is considered available for V2G, it means it is *not* available for other purposes. Therefore, for individual vehicles, vehicle-to-grid leads to autonomy loss. From a socio-technical systems perspective, this has strong implications for drivers. When considering drivers and vehicles as separate entities, vehicle availability does not only depend on the physical constraints discussed above. Ultimately, it depends on the drivers' decision to plug-in, and their actions. The amount of fuel used for vehicle-to-grid, the degree of degradation, and the loss of autonomy are factors a driver must consider when deciding whether or not to participate and if so, how. Given the heterogeneity of drivers' needs and preferences, not all vehicles can be assumed to be plugged in and available under the same conditions, as shown in the model.

8.1.3. Conceptualization of vehicle-to-grid contracts

The third sub-question, *"What rules can be used to manage vehicle-to-grid in Car as Power Plant systems?"*, was addressed in Chapter 5.

Firstly, when analyzing vehicle-to-grid transactions from a socio-technical system perspective, we concluded that the main rules or conditions to be agreed between drivers and aggregators are those regarding: time and energy availability, activation criteria and remuneration. Any set of rules regarding these aspects can be translated into a vehicle-to-grid contract. Secondly, the need for different contract types in order to engage prosumers was derived from the literature. Therefore, we proposed three contract types for vehicle-to-grid with fuel cell vehicles: price-based, volume-based and control-based contracts. Each of them comprised a distinct set of rules regarding time and energy availability, activation criteria and remuneration.

In price-based contracts, there is no explicit rule on commitment of availability. Instead, a car is available whenever it is plugged in, and the aggregator may use it until the guaranteed fuel level is reached. Therefore, the energy available depends on the fuel level at plug-in and the guaranteed fuel level. An additional constraint, however, is in the activation criteria, which is defined as the minimum price desired by the driver. Thus, the use of a car depends on the minimum price and the fuel available. This contract can be used when drivers are exposed to price fluctuations (e.g. in wholesale electricity markets). Although the remuneration depends in principle on the minimum price, a variable remuneration structure can be implemented to reward the implicit energy availability.

Volume-based contracts, on the other hand, involve a commitment of time and energy availability. Drivers agree to be plugged in during a certain time interval and make an amount of energy available to the aggregator. Outside the time interval, the driver may be plugged in but it is not available for V2G. Within the time interval, the vehicle is no longer available when the amount of volume committed has been used. To reward the commitment of plug-in time, the aggregator may remunerate the capacity made available, apart from the actual energy supplied.

With control-based contracts, there is not commitment of time or energy. A vehicle is considered available whenever it is plugged in, the aggregator may use it until the guaranteed fuel level is reached. Thus, every day, the energy available to the aggregator changes based on the fuel level at plug-in. Although there is no commitment, participation may be rewarded by remunerating the capacity made available. With the volume-based or control-based contract, the aggregator may use the fuel cell to meet the system's needs (e.g. residual demand), always respecting the fuel needs.

Each of the contract types proposed in this thesis showed different sets of rules regarding time and energy availability, activation criteria and remuneration. These reflect different agreements on the responsibilities and technical constraints for vehicle-to-grid operation. Therefore, each contract type is more suitable for certain CaPP systems and can be used to engage prosumers with different needs and preferences.

8.1.4. Performance of vehicle-to-grid contracts

Finally, we answered the fourth research sub-question: *"How do different contract types and rules affect the operation of vehicle-to-grid in Car as Power Plant systems?"*, through agent-based modeling and simulation. The effect of the proposed contracts on vehicle-to-grid transactions was explored in two types of systems: the Car as Power Plant microgrid and the Car-Park Power Plant.

In Chapter 6 we presented a CaPP microgrid with households, solar PV and wind generation, hydrogen production via electrolysis, and FCEVs as power plants. Given the reliability objective in this microgrid, we implemented volume-based and control-based contracts. The effect of different implementation strategies for each contract type was compared. To determine the performance from a socio-technical system perspective, a multi-criteria assessment was used. This allowed us to observe how the choice of rules affects the economic, reliability and driver autonomy performance in the system.

The results showed the relationship between the amount of vehicle-to-grid supplied and the contract types. Contract implementations that led to highest system reliability also had the highest economic performance, at the expense of drivers' autonomy. Moreover, when removing capacity payments, it proved to have a big influence on the drivers' average profit while reducing costs for households to a smaller extent. While it did not change the comparative performance of contract implementations, this showed the importance of defining a suitable capacity payment to reward availability for reliability purposes. The comparative performance of each contract implementation was also affected by the definition of the criteria. Using the same indicators grouped into different criteria also affected the comparative performance of the contracts. The way in which the overall performance of such a microgrid is evaluated will eventually depend on the actors involved in the design process. Therefore, knowing the interests of actors can help make decisions about the goal of the system, the type of contract needed and how it can be implemented.

In Chapter 7, we modeled a car park used by FCEV drivers that participate in the wholesale electricity market through an aggregator, using price-based contracts. Hydrogen production in the car park was also modeled and the price was updated based on total costs and the amount of hydrogen produced. For this case, the remuneration structure was defined as the contractual minimum price plus a variable profit margin, calculated as a function of the fuel availability. We analyzed the effect of this contract type on the Car-Park Power Plant and the actors' economic performances in three renewable energy scenarios and with two different dispatch rules.

The results showed that using price-based contracts, the supply of vehicle-to-grid increased under increasing market price scenarios. The profit potential for drivers proved to be quite variable in all energy scenarios, and the dispatch rule used by the aggregator proved to influence the distribution of revenues among drivers. Since all drivers used the cost of vehicle-to-grid as the minimum price, the variability in annual drivers' profits was explained in the differences in driving schedule and availability. Due to fluctuating electricity prices, the prices to which drivers were exposed were different every time they were in the car park. Changing hydrogen prices also led to fluctuations in individual minimum prices, which affected the drivers' revenues, albeit to a smaller extent. Increasing the minimum price by a small percentage reduced profits for all drivers significantly. Given the fluctuating nature of electricity prices, the relationship between driver's (time) availability and profit was explored, namely the drivers' parking duration, arrival time and parking profile. While one can deduce intuitively that parking duration influences the chances to supply V2G, the arrival time also proved to be important, due to the limited number of V2G dischargers in the car park. Moreover, the availability of other vehicles also affected drivers' chances to supply V2G. Due to the minimum offer volume in the market, vehicles could only be dispatched in groups of ten. The model demonstrated the importance of analyzing drivers' profit potential in electricity markets from a socio-technical systems view. The effect of minimum prices, driver characteristics, and aggregator strategies on the performance of all drivers showed the importance of considering the characteristics individual actors when analyzing the economic potential of vehicle-to-grid supply in electricity markets.

In conclusion, the formalization of vehicle-to-grid contracts in agent-based models allowed a better understanding of their role in CaPP systems. By implementing the contracts in models, different strategies for implementation and aggregator strategies were also considered and explored. The contracts explored in this research needs to be part of the design process of systems with vehicle-to-grid. The models built and used in this thesis can be used to further answer what-if questions about aggregators and drivers' strategies.

8.2. Conditions for CaPP development

In this thesis we have focused on the role of vehicle-to-grid contracts in the operation of two types of future Car as Power Plant systems. When building the models, assumptions were made on certain developments that are needed to enabled the emergence of these systems. From a socio-technical system perspective, this emergence is expected to be influenced by inter-dependent developments, some of which we discuss below.

Institutional conditions for vehicle-to-grid

The literature review indicated that formal institutions from Layer 2 have an influence on the implementation of vehicle-to-grid. However, this was not the focus of this thesis and therefore was not analyzed in detail in the models. The underlying assumptions in the two agent-based models and in the V2G contract conceptualization was that the required formal institutions are in place to allow vehicle-to-grid transactions. While the operational aspects of V2G can provide insights about the feasibility of vehicle-to-grid within CaPP systems, the right institutional conditions are needed to enable it. At the moment V2G has only been tested in controlled environments. It is not yet formally considered another form of distributed energy resource. Therefore, there are still questions about how the remuneration of V2G should be defined, whether it should be different for each type of electric vehicle, and/or whether it should be regulated. In this thesis, different remuneration structures with fixed and variable energy remuneration were explored. The importance of defining a suitable capacity remuneration was also discussed.

In the two models, we assumed CaPP systems were integrated in low-carbon electricity systems. In a future with increasing variable renewable energy sources, vehicle-to-grid with fuel cell cars can become valuable. However, in systems with more traditional sources it would be difficult to prove its value. This would impede the right institutional conditions to be developed for the implementation of vehicle-to-grid.

Development of a hydrogen economy

The introduction of hydrogen in the energy and transport systems is undoubtedly an important factor in the development of the Car as Power Plant. The role of hydrogen in future energy systems is slowly being recognized in Europe and in Asia. The developments, however, differ substantially in the underlying motivations. As such, the introduction of hydrogen as another energy carrier may occur at different paces.

In Europe, a hydrogen economy is set to emerge slowly. The need for hydrogen is tied to the increase of variable renewable energy sources in the electricity systems. In this context, hydrogen is viewed as an energy carrier that can help cope with increasingly variable and unpredictable renewable generation. This leads not only to short-term variability, but also to seasonal and year to year fluctuations of residual demand. Therefore, using hydrogen as storage and re-electrifying it through fuel cells (or using it for other purposes) can support the further decarbonization of electricity and energy systems in Europe. Although stationary fuel cell systems could be used, an increasing adoption of FCEVs can help the establishment of a hydrogen economy by driving investments in the required infrastructure for storing and transporting hydrogen.

In Japan, a future ‘hydrogen society’ is being considered after the Fukushima disaster, as a means to deal with security of supply and reduce dependence on fossil fuel imports. It is being promoted directly by the government, through incentives for the development of a hydrogen infrastructure. This has already led to the construction of a hundred tank stations nation-wide. Fuel cell vehicles are also being promoted, according to experts, to increase the acceptability and use of hydrogen by consumers. The government has set a plan to develop a hydrogen society - based first on the use of hydrogen produced from fossil fuels. The use of local renewable power-to-hydrogen technologies and imports of hydrogen produced brown coal and carbon capture and storage (CCS) from Australia is also envisioned for the future. This would allow the cost of hydrogen to be reduced from the current by a fifth after 2030. With hydrogen at the center of electricity systems, some experts claim that to achieve security of supply, hydrogen should be used in centralized power plants rather than in vehicles. Therefore, even with an established hydrogen economy, they use of fuel cell vehicles for driving and as distributed flexibility resources is not deemed necessary.

Adoption and participation

This thesis assumes that a certain level of FCEV adoption has been reached in the future CaPP systems analyzed. The development of CaPP systems depends on FCEV adoption and the willingness of drivers to become prosumers. These two aspects are not explored in this thesis. The adoption of FCEV will determine whether such integrated energy and transport systems can be developed. With the currently low adoption levels worldwide, there are some key barriers in FCEV adoption such as the cost, the lack of hydrogen infrastructures and the acceptance of hydrogen as a safe energy carrier. These barriers will undoubtedly play an important role in the feasibility of CaPP systems.

The adoption of FCEVs does not guarantee a certain level of vehicle-to-grid participation. As a new type of energy practice, it may bring uncertainties to drivers. While BEVs have to plug-in their vehicles to charge their batteries, FCEVs only need to refill at tank stations. Therefore, the plug-in behavior is not part of the FCEV 'driving experience'. To engage drivers in vehicle-to-grid, they first have to understand what is expected from them and in exchange for a certain revenue level. To this end, vehicle-to-grid contracts can be useful in communicating to drivers the implications of participating, and the possible level of profit depending on the system. Additionally, three contract types we explored can engage drivers with different needs and preferences. If the implications of V2G participation become clear for drivers, the possibility of earning revenues while parked could also stimulate the adoption of FCEVs. This would depend on further developments in the integration of the mobility and electricity sectors. Given the current trends in electric mobility, the successful implementation of V2G with battery electric vehicles would have a positive influence on the adoption potential of FCEVs.

Technological development

The techno-economic characteristics used in the two models are based on expert projections for 2050. This affects the performance of CaPP systems and the costs of hydrogen and vehicle-to-grid. Under the current conditions, the level of hydrogen production in the electrolyzers would be lower, and the amount of fuel used for each kWh of V2G will be higher.

In the models, the required ICT technologies are assumed to be in the CaPP systems, although not explicitly discussed. This is necessary to enable the communication between aggregators and drivers. This includes on-board technology to measure and communicate energy levels and driver preferences, as well as contract parameters. To this end, privacy concerns have to be addressed due to the amount of data that an aggregator would have access to. Contracts can also be implemented on blockchain platforms, given that parameters can be coded, as shown in the agent-based models. In systems like the CaPP microgrid, the energy management system could be built on blockchain platform, to manage all transactions in a peer-to-peer governance structure. In this context, contracts would become self-executing and/or self-enforcing and therefore the proper measures should be implemented to penalize possible deviations from the agreed conditions.

Battery and fuel cell electric vehicles

As discussed in Chapter 1 of this thesis, BEVs and FCEVs are usually seen as competitive technologies. This often leads to the question of which can better support the transition towards clean electricity systems through V2G. In the narrow sense of the CaPP concept - and in this thesis - we only focused on FCEVs because the main goal was to understand the role of hydrogen and FCEVs in future electricity systems.

In the context of the CaPP project, Sahu, Park Lee, and Lukszo (2018) explored the use of BEVs vs. FCEVs in a future CaPP smart city. The results show that since BEVs use electricity directly from the grid, they increase the residual load. Moreover, the time needed for charging makes them unavailable for V2G. In the absence of smart charging, the overall availability of BEVs for V2G is reduced by 27 to 30% with respect to scenarios in which only FCEVs are used. Since they were considered separately in this case, we need to further explore the combined role of BEVs (with smart charging and V2G) and FCEVs (V2G) and uncover possible synergies. The further stage of development, commercialization and adoption of BEVs means that lessons on vehicle-to-grid implementation with BEVs can positively influence the developments in FCEV adoption and the Car as Power Plant.

8.3. Discussion and reflections

Socio-technical system operation framework

In this thesis we analyzed the institutions needed for V2G transactions using a socio-technical system operation framework. With this framework, the concept of V2G operation is no longer considered just a physical process. The actors involved and their interactions, governed by institutions (rules), are also included to understand a V2G transaction as a combination of actions, rules, and physical processes.

Applied to the research of CaPP systems and vehicle-to-grid in general, this framework helped understand better the integration of the electricity and mobility systems. It provided insights on the complexities of vehicle-to-grid operation, by considering cars as physical artefacts owned and used by individual drivers. As such, the real potential of vehicle-to-grid in electricity system was proved to also depend on the different needs and preferences of these drivers. Moreover, it showed that the aggregated operational capacity is variable and uncertain to some extent, even though FCEVs are dispatchable flexibility sources. To this end, contracts can help reduce uncertainties in the operation of vehicle-to-grid. The framework helped gain a wider understanding of the system operation. Additionally, its formalization in models aided the quantification of the effect of contracts in the system and the implications for drivers. As discussed, this view of the system provides a wider perspective than the one typically used in the vehicle-to-grid literature, which focuses on either analyzing the physical system operation or the techno-economic characteristics of V2G integration.

Beyond the Car as Power Plant concept, this framework can also be used to analyze the implementation of innovative technologies, especially when heterogeneous actors are involved. Analyzing the operation of innovative systems from a socio-technical perspective can help better understand the roles and responsibilities of actors in the system and therefore the new rules needed.

Conceptualization of V2G contracts

As discussed in the literature review, the use of contracts for V2G has been previously explored. However, contract parameters are usually limited to the plug-in duration and guaranteed energy level after V2G. This is not only insufficient for describing vehicle-to-grid with fuel cell vehicles, but also for engaging drivers in different types of V2G supply. By analyzing the vehicle-to-grid operation from a socio-technical system perspective, we identified the main conditions to be agreed upon between driver and aggregator: time and energy availability, activation criteria, and remuneration. From the demand-side management literature we proposed three unique contract types: price-based, volume-based and control-based contracts.

The contracts conceptualized in this thesis can be used to explore the integration of V2G with other electric drive vehicles in different systems and markets. In the case of battery electric vehicles, the conditions for demand response through smart charging can also be incorporated in each one of the contract types. Thus, contracts to use *BEVs as flexibility sources* can be designed. On the other hand, these contracts can also be modified to simply manage smart charging transactions, by adjusting the parameters accordingly.

Formalization of contracts in agent-based models

The operationalization of contracts provides important insights for vehicle-to-grid implementation. While vehicle-to-grid contracts have been discussed previously, their formalization in agent-based models is new. It allows combining the physical system operation with the actors' decisions and the explicit definition of all contract parameters. Therefore, this approach helped quantify the effect of contracts on the aggregated V2G capacity and the performance of every driver. The role of contracts for the integration of vehicle-to-grid cannot be fully understood without taking into account the heterogeneous drivers, their characteristics, behavior and the individual contracts. Agent-based modeling and simulation proved to be the appropriate tool to do this.

Using the framework of this thesis to explore CaPP systems through agent-based modeling and simulation led to some limitations. As discussed in the corresponding chapters, in order to focus on all three system components and their interactions, some simplifications were needed. Nevertheless, for the purpose of this research and for answering the modeling questions, the assumptions were considered to be acceptable after an expert validation.

8.4. Recommendations

8.4.1. Future research

To further understand how contract types can affect the aggregated V2G operation, the model can be enriched with data of drivers' preferences and willingness to participate. A choice experiment can be carried out to find out what type of contract is preferred and what parameters are considered most important by certain groups of drivers. Similarly, the type and level of remuneration that can motivate drivers to participate can also be determined. To do this, the survey should explain the implications for V2G participation to drivers: increased refilling needs, commitment of plug-in time in some cases, degradation of fuel cell due to V2G, etc. The models and outcomes of this thesis can be used to help respondents understand these implications, especially given the lack of experiences in the real world. If possible, pilot projects that involve V2G should extensively explore user experiences in order to form a better picture about the practical aspects of V2G participation and thus complement the insights of this thesis.

To further enrich the modeling of drivers in CaPP models, the mobility aspect can be improved. Drivers were assumed to have a fixed daily driving schedules, with possible variability of up to two hours, and fixed daily distances. However, actual driving behavior is more variable and less predictable. The possibility of unplanned trips, or different day-to-day driving distances and schedules could affect the analysis of vehicle-to-grid. A more detailed analysis of the driving behavior of actors could help identify other challenges or opportunities for vehicle-to-grid implementation. Moreover, the combination of passenger and light-duty vehicles could be considered to better understand the potential of FCEVs, considering they have different use patterns and availability profiles.

The models presented in this thesis can be extended by modeling the aggregator in more detail. This includes modeling the availability of a portfolio of flexibility resources and the optimization techniques that the aggregator may use to participate in several markets. For example, in the Car-Park Power Plant model, the aggregator could use FCEVs and BEVs to participate in the day-ahead, intraday and balancing markets. Incorporating the perspective of the aggregator in more detail will help understand the real impact of CaPP systems in the future. Therefore, it can help identify where the value of fuel cell vehicles and the CaPP concept lie in future low-carbon electricity systems.

The operational models built in this thesis can be used to make strategic or long term analyses. What-if scenarios with the conditions for the development of the Car as Power Plant discussed previously can be tested in combination. Thus, the effect of certain policies, or the rate of FCEV adoption can be analyzed to draw conclusions on its long-term development. Similarly, the effects of the system operation and performance on long-term developments could be tested. To explore the emergence of CaPP systems in the long term, the interactions between physical system, network of actors and institutions have to be explicitly considered as well. As discussed above, the developments in all parts of the socio-technical system affect each other. To do this, multi-level models can be built to include actions on the short term and the effect of policy decisions on the long term.

8.4.2. Considerations for implementation

Beyond the Car as Power Plant concept, we can draw some lessons from this research for the implementation vehicle-to-grid with all kinds of electric vehicles. Firstly, the three contract types proposed in this thesis can be used to engage drivers with different needs and preferences. They can help aggregators find the appropriate participants for certain markets. As seen in the two models, they also provide a structure on which incentives or remuneration structures can be designed to reward time and energy availability.

Secondly, a certain level of profit from vehicle-to-grid cannot be ensured to drivers. The second model showed that opportunities to participate depend on the availability of discharging poles, the fluctuating electricity prices and the availability of other vehicles at the time. With the increasing year-to-year variability of residual demand in future low-carbon systems, drivers may not be able to profit at all in some years while they earn more than expected in others. Thus, to reduce this risk, aggregators could use vehicles to participate mostly in balancing markets where at least the capacity remuneration will be as expected. Finally, the appropriate level of capacity remuneration should be determined. As distributed flexibility resources, the value of vehicle availability could be quantified by analyzing the avoided network expansion costs. This capacity remuneration could be regulated to ensure that electric vehicles participate under the same conditions in all parts of the national electricity system.

Developments in technology and may change the vehicle-to-grid concept explored in this thesis. While it was not discussed, the rise of autonomous driving can change the value of vehicle-to-grid by allowing the transport of energy to locations where it is needed. This, combined with different types of vehicle ownership, would change the structure and role of contracts proposed in this thesis. In this context, large fleets of rental vehicles with autonomous driving capabilities would involve different rules for drivers. For example, drivers could be allowed to use the vehicle for driving without interfering with the vehicle-to-grid schedules. This would involve not only a plug-in schedule but also ensuring there is enough energy in the car before plugging in.

Another major development that would affect the current vehicle-to-grid concept is the possibility of using direct hydrogen inlets in fuel cell car. This would allow aggregators to exploit the capacity of vehicles without using hydrogen from the vehicles' tanks. In this case, the energy availability aspects would become less relevant and the time availability more critical. Moreover, it would be more important to monitor degradation in the fuel cells as fuel availability would no longer limit the operation of the fuel cell stack. In this case, the remuneration would consist of the capacity payment and an energy payment corresponding to degradation costs.

Furthermore, policy implications can be drawn from this research. To recognize electric vehicles as flexible distributed energy resources, appropriate remuneration levels have to be defined. This means regulating the minimum and maximum capacity price every vehicle could receive to make the car available, depending on the conditions of the system. Moreover, regulators must ensure that drivers are sufficiently remunerated for every kilowatt hour they provide, to reduce drivers' risks. Regulating V2G remuneration implies that the government has to prioritize the role of electric vehicles in future electricity systems, and explore measures to support sector coupling. Considering the synergies that could be achieved, the adoption and diffusion of FCEVs and other types of electric vehicles should be financially supported, as a strategy to accelerate the decarbonization of both sectors.

Moreover, the identification of hydrogen as an energy carrier in future systems by the government is key in the adoption of FCEVs. The pathway set by the Japanese government has advanced the development of a hydrogen infrastructure and FCEV adoption in the country in the recent years. Moreover, Japan's future plans of importing brown and green hydrogen from Australia have stimulated the Australian government to explore the role of hydrogen in their country. This has enabled the prioritization of investments to unlock the potential of hydrogen. While a certain level of FCEV adopters are needed for expanding hydrogen infrastructures, there are more potential uses for hydrogen, as natural gas networks can be used to store and transport it, even to households. Therefore, the support of hydrogen in the form of investments or subsidies would greatly reduce the uncertainties for FCEV adoption. The diffusion of FCEVs would also increase the interest and potential of V2G, since it would enable the re-electrification of green hydrogen in the electricity systems.

8.4.3. Final remarks

In a world with energy systems in transition, this thesis provides a view of how fuel cell cars could be used for vehicle-to-grid in future CaPP systems. All on-going and future developments in electric mobility, hydrogen economy, electricity systems, and people's attitudes and behaviors will determine whether or not these systems materialize. Given the clear potential of hydrogen and V2G in our future systems, sector coupling through hydrogen and FCEVs needs to be further prioritized in order to accelerate the energy transition. Supporting and enabling sector coupling could bring synergies that cannot be achieved when they are not combined.

This thesis provides insights for the development of CaPP systems, focusing especially on how to leverage FCEVs as power plants using vehicle-to-grid contracts. We conceptualized three contract types as unique sets of rules that can be used to operate FCEVs in CaPP systems. Our work shows that rules regarding time and energy availability, activation criteria and remuneration for V2G have to be clearly defined to reduce uncertainties in driver participation. The effect of these rules and contract types was extensively explored through simulation of agent-based models built in Python. The quantitative insights obtained through these simulations show the importance of considering the extent to which drivers want to engage in V2G to analyze the potential of V2G in the future. The conditions of the contract parameters represent further constraints in driver availability. Therefore, this work underscores the importance in understanding driver participation to estimate the potential capacity available for V2G. The three contracts provide sets of rules that are appropriate to different driver preferences as well as system needs. The contract types proposed and explored in this thesis are also suitable for coordinating V2G with battery electric vehicles. They provide a base structure upon which the conditions for smart charging can be added.

The multidisciplinary approach used in this thesis provides unique insights for the development of the Car as Power Plant and for exploring other systems with innovative technologies. A techno-economic analysis of the Car as Power Plant can show whether the system design is feasible, and the insights can be supported by considering the controllability of the system. However, the socio-technical system perspective on the Car as Power Plant further enriches these analyses by bringing into light its inherent complexity (Farahani et al., 2019). Our work explores the new rules are necessary to guide interactions between actors and to define the conditions for using FCEVs for V2G, hereby reducing uncertainties in the system operation. More importantly, we show that the effects of new rules for V2G in the system can only be understood if they are operationalized and analyzed quantitatively. The results demonstrate that the approach used in this thesis is necessary to provide a more comprehensive view on the feasibility of innovative technologies, as all innovations require new rules. As such, this work emphasizes the value of analyzing new technologies from a socio-technical system operation perspective, and demonstrates that operationalizing and testing new institutions in simulation models provides important insights on the complexities of bringing innovative technologies into being.

A

Car as Power Plant microgrid model

This appendix contains more details describing the agent-based model presented in Chapter 6, the Car as Power Plant microgrid. First, the complete list of driver and microgrid operator variables are presented, followed by the equations used to calculate the total costs of electricity and hydrogen. Then, the model verification shows the different tests performed to verify the agent-based model.

A.1. Driver and microgrid operator variables

Table A.2: Microgrid operator agent variables

Variable	Description	Data type
	Contracted drivers and households	
drivers_list	List of contracted drivers	Object (list)
households_list	List of contracted households	Object (list)
	System balance and V2G	
aggregatedLoad	Load from all households in current time step	Float
aggregatedPV	Aggregated PV generation	Float
aggregatedV2G	Aggregated V2G power in current time step	Float
imbalance	Imbalance of supply and demand in current time step	Float
resLoad	Residual load in current time step	Float
availableFCEVs	Number of vehicles that can be used for V2G	Integer
requiredFCEVs	Number of vehicles that are needed to serve the residual load	Integer
dispatchedFCEVs	Number of vehicles used for V2G	Integer
dispatchedFCEVs_t	Number of vehicles used for V2G at every time step	Integer
numFCEVsHere	Number of vehicles in the neighborhood	Integer
pExport	Power exported in current time step	Float
pImport	Power imported in current time step	Float
isV2G_t	State of V2G operation in microgrid at every time step	Integer (list)
PoP	Preferred operating point of individual FCEVs	Integer
PVtoLoad	PV generated used in household loads in current step	Float
PVexcess	Excess PV generation in current time step	Float
totalAggregatedLoad	Total aggregated load from households at the end of the simulation	Float

Continued on next page

TableA.2 – *Continued*

Variable	Description	Data type
totalPVtoLoad	Total PV generation used in household loads at the end of the simulation	Float
totalPVexcess	Total excess PV generation the end of the simulation	Float
totalAggregatedPV	Total aggregated PV generation at the end of the simulation	Float
totalPexport	Total power exported at the end of the simulation	Float
totalPimport	Total power imported at the end of the simulation	Float
totalAggregatedV2G	Total aggregated vehicle-to-grid supply at the end of the simulation	Float
totalResLoad	Total residual load at the end of the simulation	Float
	Techno-economic variables and contract management	
avgEvalProfit	Average drivers' profit during evaluation period	Float
driversEvalProfit	Total drivers' profits during evaluation period	Float
isAdjustContract	Status indicating changes in V2G contracts	Boolean
elecContractCost	Annual contract cost for electricity supply in households	Float
elecPrice	Electricity price in current time step	Float
elecPriceImport	Component of electricity price from electricity imports	Float
elecPricePV	Component of electricity price from PV generation	Float
elecPriceV2G	Component of electricity price from vehicle-to-grid	Float
electricityCostsImport	Cost of importing electricity in current time step	Float
electricityCostsV2G	Cost of V2G supply in current time step	Float
electricityCostsV2GC	Capacity costs for V2G in current time step	Float
electricityCostsV2GE	Energy costs for V2G in current time step	Float
electricityRevenuesHouseholds	Revenues from electricity consumption in households, in current time step	Float
electricityRevenuesExport	Revenues from electricity exports in current time step	Float
evalTimer	Timer for evaluation	Integer
hydrogenCostsImport	Costs from hydrogen imports in current time step	Float
hydrogenPrice	Hydrogen price in the system	Float
hydrogenRevenuesExport	Revenues from hydrogen export in current time step	Float
hydrogenRevenuesRefilling	Revenues from hydrogen refilling in current time step	Float
V2Gprice	Price for 1 kWh of V2G supplied	Float
totalElectricityCostsImport	Total costs from electricity imports	Float
totalElectricityCostsV2G	Total costs from V2G	Float
totalElectricityCostsV2GC	Total costs from V2G capacity payments	Float
totalElectricityCostsV2GE	Total costs from V2G supplied	Float
totalElectricityNetProfit	Total net profit from electricity supply	Float
totalElectricityRevenuesExport	Total revenues from electricity exports	Float
totalElectricityRevenuesHouseholds	Total revenues from electricity supply to households	Float
totalHydrogenCostsImport	Total costs hydrogen imports	Float (list)
totalHydrogenNetProfit	Total net profit from hydrogen generation and supply	Float
totalHydrogenRevenuesRefilling	Total revenues from hydrogen refilling	Float
totalHydrogenRevenuesExport	Total revenues from hydrogen exports	Float
totalHydrogenCostsImport	Total costs from hydrogen imports	Float
	PV system and Wind-Electrolyzer-Storage system	
hSystem	Hydrogen conversion and storage system	Object
PVsystem	PV system	Object
windSystem	Wind system	Object
	Total Costs and SLCoH, LCoE calculation	
CCelUnit	Electrolyzer capital cost per unit	Float
LTel	Lifetime of electrolyzer	Integer
OMCelPerc	Electrolyzer operation and maintenance costs	Float
CCel	Annual electrolyzer capital costs	Float
OMCel	Annual operation and maintenance costs of electrolyzer	FFloat
TCel	Total costs electrolyzer	Float
CChsUnit	Hydrogen storage capital cost per unit	Float
LThs	Lifetime of hydrogen storage	Float
OMChsPerc	Hydrogen storage operation and maintenance costs	Float
CChs	Annual hydrogen storage capital costs	Float
OMChs	Annual operation and maintenance costs of hydrogen storage	Float
TChs	Total costs hydrogen storage	Float
CCcUnit	Compressor capital cost per unit	Float
LTc	Lifetime of compressor	Float
OMCcPerc	Compressor operation and maintenance costs	Float
CCc	Annual compressor capital costs	Float

Continued on next page

TableA.2 – *Continued*

Variable	Description	Data type
`OMCc`	Annual operation and maintenance costs of compressor	Float
`TCc`	Total costs compressor	Float
`CCdUnit`	Dispenser capital cost per unit	Float
`LTd`	Lifetime of dispenser	Float
`OMCdPerc`	Dispenser operation and maintenance costs	Float
`CCd`	Annual dispenser capital costs	Float
`OMCd`	Annual operation and maintenance costs of dispenser	Float
`TCd`	Total costs dispenser	Float
`CCrwUnit`	Rainwater collector capital cost per unit	Float
`LTrw`	Lifetime of rainwater collector	Float
`OMCrwPerc`	Rainwater collector operation and maintenance costs	Float
`CCrw`	Annual rainwater collector capital costs	Float
`OMCrw`	Annual operation and maintenance costs of rainwater collector	Float
`TCrw`	Total costs rainwater collector	Float
`CCroUnit`	Reverse osmosis capital cost per unit	Float
`LTro`	Lifetime of reverse osmosis	Float
`OMCroPerc`	Reverse osmosis operation and maintenance costs	Float
`CCro`	Annual reverse osmosis capital costs	Float
`OMCro`	Annual operation and maintenance costs of reverse osmosis	Float
`TCro`	Total costs reverse osmosis	Float
`CCpvUnit`	PV system capital cost per unit	Float
`LTpv`	Lifetime of PV system	Float
`OMCpvPerc`	PV system operation and maintenance costs	Float
`CCpv`	Annual PV system capital costs	Float
`OMCpv`	Annual operation and maintenance costs ofPV system	Float
`TCpv`	Total costs PV system	Float
`CCwtUnit`	Wind turbine capital cost per unit	Float
`LTwt`	Lifetime of wind turbine	Float
`OMCwtPerc`	Wind turbine operation and maintenance costs	Float
`CCwt`	Annual wind turbine capital costs	Float
`OMCwt`	Annual operation and maintenance costs of wind turbine	Float
`TCwt`	Total costs wind turbine	Float
`CCdisUnit`	4-point V2G discharger poles capital cost per unit	Float
`LTdis`	Lifetime of discharger	Float
`OMCdisPerc`	Discharger operation and maintenance costs	Float
`CCdis`	Annual discharger capital costs	Float
`OMCdis`	Annual operation and maintenance costs of discharger	Float
`TCdis`	Total costs V2G discharger poles	Float
`LCOE`	Levelized cost of PV electricity	Float
`SLCOH`	System levelized cost of hydrogen	Float
`TChydrogen`	Total annual costs of hydrogen	Float

A.2. Total costs of electricity and hydrogen

To calculate the system levelized cost of hydrogen, we calculate the total costs of the system taking into account the following components: 1) wind turbine, 2) electrolyzer, 3) reverse osmosis, 4) rainwater collector, 4) hydrogen storage, 5) hydrogen compressor, and 6) hydrogen dispenser.
Total costs of electrolyzer (el):

$$TC_{el} = CC_{el} + OMC_{el} \tag{A.1}$$

$$CC_{el} = CC_{el}^{unit} \cdot P_{el}^{max} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{el}}}{((1 + WACC)^{LT_{el}} - 1)} \tag{A.2}$$

$$OMC_{el} = CC_{el}^{unit} \cdot P_{el}^{max} \cdot OMC_{el}^{\%} \tag{A.3}$$

Total costs of wind turbine (wt):

$$TC_{wt} = CC_{wt} + OMC_{wt} \tag{A.4}$$

$$CC_{wt} = CC_{wt}^{unit} \cdot P_{wt} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{wt}}}{((1 + WACC)^{LT_{wt}} - 1)} \tag{A.5}$$

$$OMC_{wt} = CC_{wt}^{unit} \cdot P_{wt} \cdot OMC_{wt}^{\%} \tag{A.6}$$

Total costs of hydrogen storage (HS):

$$TC_{HS} = CC_{HS} + OMC_{HS} \tag{A.7}$$

$$CC_{HS} = CC_{HS}^{unit} \cdot H_{HS}^{max} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{HS}}}{((1 + WACC)^{LT_{HS}} - 1)} \tag{A.8}$$

$$OMC_{HS} = CC_{HS}^{unit} \cdot H_{HS}^{max} \cdot OMC_{HS}^{\%} \tag{A.9}$$

Total costs of compressor (c):

$$TC_{c} = CC_{c} + OMC_{c} \tag{A.10}$$

$$CC_{c} = \frac{CC_{c}^{unit}}{HHV} \cdot P_{el}^{max} \cdot \eta_{el} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{c}}}{((1 + WACC)^{LT_{c}} - 1)} \tag{A.11}$$

$$OMC_{c} = \frac{CC_{c}^{unit}}{HHV} \cdot P_{el}^{max} \cdot \eta_{el} \cdot OMC_{c}^{\%} \tag{A.12}$$

Total costs of dispenser (d):

$$TC_{d} = CC_{d} + OMC_{d} \tag{A.13}$$

$$CC_{d} = CC_{d}^{unit} \cdot N_{d}^{max} \cdot \frac{WACC \cdot (1 + WACC)^{LT_{d}}}{((1 + WACC)^{LT_{d}} - 1)} \tag{A.14}$$

$$OMC_{d} = CC_{d}^{unit} \cdot N_{d}^{max} \cdot OMC_{d}^{\%} \tag{A.15}$$

Total costs of rain water collector (rw):

$$TC_{rw} = CC_{rw} + OMC_{rw} \tag{A.16}$$

$$CC_{rw} = CC_{rw}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot \frac{24}{1000} \cdot \frac{WACC \cdot (1+WACC)^{LT_{rw}}}{((1+WACC)^{LT_{rw}} - 1)} \tag{A.17}$$

$$OMC_{rw} = CC_{rw}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot \frac{24}{1000} \cdot OMC_{rw}^{\%} \tag{A.18}$$

Total costs of reverse osmosis (ro):

$$TC_{ro} = CC_{ro} + OMC_{ro} \tag{A.19}$$

$$CC_{ro} = CC_{ro}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot 24 \cdot \frac{WACC \cdot (1+WACC)^{LT_{ro}}}{((1+WACC)^{LT_{ro}} - 1)} \tag{A.20}$$

$$OMC_{rw} = CC_{ro}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot 24 \cdot OMC_{rw}^{\%} \tag{A.21}$$

Total costs of PV electricity:

$$TC_{PV} = CC_{PV} + OMC_{PV} \tag{A.22}$$

$$CC_{PV} = CC_{PV}^{unit} \cdot P_{PV} \cdot \frac{WACC \cdot (1+WACC)^{LT_{PV}}}{((1+WACC)^{LT_{PV}} - 1)} \tag{A.23}$$

$$OMC_{PV} = CC_{PV}^{unit} \cdot P_{PV} \cdot OMC_{PV}^{\%} \tag{A.24}$$

The costs of 4-point V2G dischargers (dis) are defined as:

$$TC_{dis} = CC_{dis} + OMC_{dis} \tag{A.25}$$

$$CC_{dis} = CC_{dis}^{unit} \cdot N_{dis} \cdot \frac{WACC \cdot (1+WACC)^{LT_{dis}}}{((1+WACC)^{LT_{dis}} - 1)} \tag{A.26}$$

$$OMC_{dis} = CC_{dis}^{unit} \cdot N_{dis} \cdot OMC_{dis}^{\%} \tag{A.27}$$

A.3. Model verification

A.3.1. Single-agent testing

To test a single driver agent we followed its states and verify whether they change as expected. There are 3 agent types in the model: the driver, the microgrid operator and the households. Since the microgrid components are owned and controlled by the microgrid operator, it needs to be created even in the single-agent testing. However, interactions are avoided by not creating household agents. Energy consumption from households involves indirect interaction between them and drivers, since it defines demand for V2G. Therefore, to test a single driver agent, we created one driver and one microgrid operator agent. The methods `makeContract`, `drive`, `refill` and `plugin` were tested. In the seasonal scenarios, the change in contract parameters was also verified. To do this, the model was run for an entire year for the four scenarios.

Make contract

For a single driver agent, we looked at the contract initialization in the four possible scenarios. In the VBC scenarios, the duration committed and maximum volume varies: it is uniformly high in the seasonal scenario and more variable in the flexible scenario. In the CBC scenarios, the minimum fuel needed at plug-in is higher in the seasonal scenario and low in the fixed scenario. In terms of the minimum fuel availability (as a fraction), the values are 0.5 and 0.1 respectively. Therefore, the initialization of the contracts is done correctly. The driver characteristics and contract parameters defined in each scenario are shown in Tables A.6 and A.7. The energy remuneration and capacity remuneration are the same in all simulations:

- `energyRemuneration`: 0.10 €/kWh
- `capacityRemuneration`: 0.01 €/kW-h

Drive, Refill, Plug-in

The drivers' daily actions can be observed following the change in state (drive, refill, plug-in, V2G) and the level of hydrogen in the tank. In the single-agent test, there are no household agents and therefore no V2G demand. Thus, we observed whether the drive, refill and plug-in methods were carried out as expected. In volume-based scenarios, the driving occurs at the same time every day. The plug-in hours are also fixed and limited to the contract parameters. The refilling occurs before plugging in, when necessary. Figure A.1 shows the hydrogen level and the states of a single driver agent in the two VBC scenarios, throughout the first week. A car is plugged in only the hours that are indicated by the contract parameters.

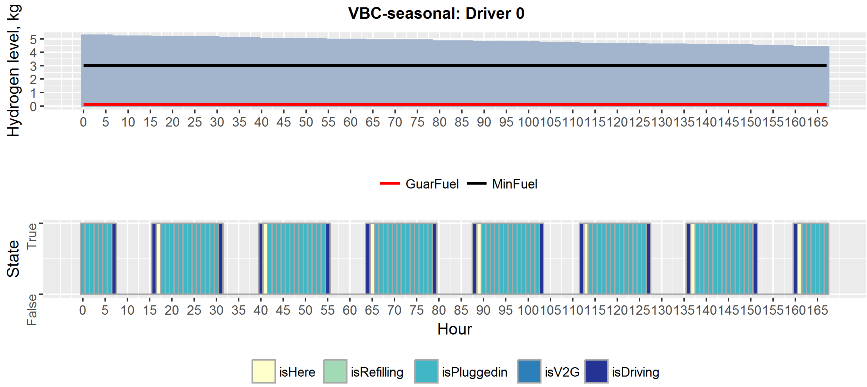
In control-based scenarios, the driving occurs around the same time every day, with a +-1 hour variation. The plug-in hours are defined by the fuel available and the hours of parking. The refilling occurs before plugging in, when necessary. Figure A.2 shows the hydrogen level and the states of a single driver agent throughout the first week. The vehicles are plugged in whenever there is enough fuel, until departure.

VBC and CBC-seasonal: Adjust seasonal contract

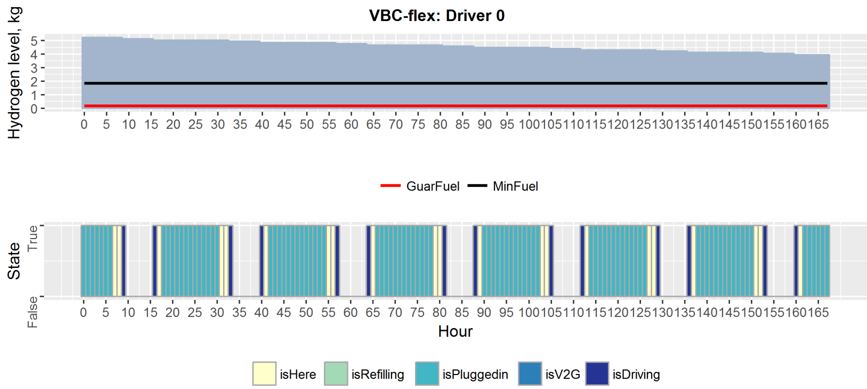
In the seasonal scenarios, the contract parameters are adjusted seasonally, independently from a driver's performance. Table A.4 shows the change in parameters in the VBC-seasonal scenario. According to Table 6.14, a `minFuelAvailability` of 0.50 is used to calculate the initial maximum volumes. However, since `maxVolume` can only be a factor of 10 (due to `PoP`), the actual `minFuelAvailability` is recalculated. This measure helps to compare more easily the amount of volume committed per driver. Table A.5 shows the change in parameters of a driver agent in the CBC-seasonal scenario. As expected, in both scenarios, the parameters are reduced by 70%.

A.3.2. Interaction testing in minimal model

In the minimal model 1 household agent, 1 microgrid operator agent and 2 driver agents are created. This allows for interactions between and within the agent types to occur,

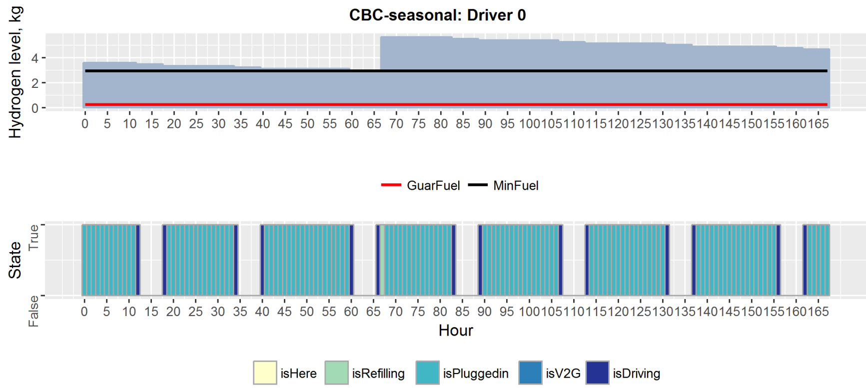


(a) VBC-seasonal

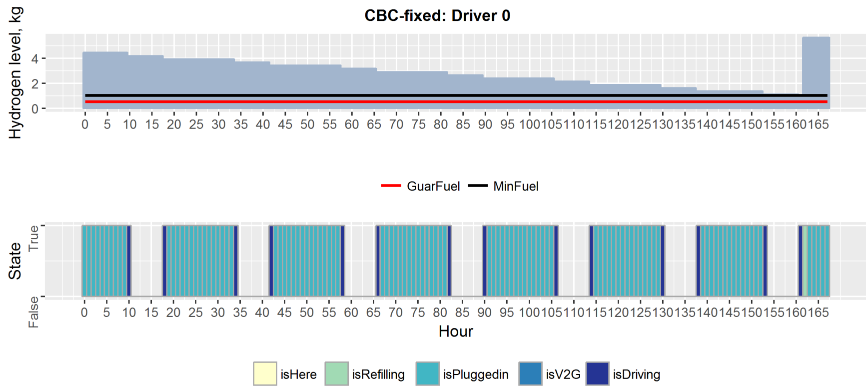


(b) VBC-flexible

Figure A.1: Hydrogen level and states of two FCEVs throughout the first week



(a) CBC-seasonal



(b) CBC-fixed

Figure A.2: Hydrogen level and states of two FCEVs throughout the first week

Table A.1: Driver agent variables

Variable	Description	Data type
	Driver properties	
`arrival`	Arrival time at car park	Integer
`departure`	Departure time from car park	Integer
`distance`	Daily distance traveled	Integer
`drivingVariability`	Number of hours by which the arrival and departure times are changed	Integer
`isAdjustContract`	State indicating whether the driver is changing its contract parameters (VBC)	Boolean
`isAdjustRefill`	State indicating whether the driver is changing its refill strategy (CBC)	Boolean
`minFuelDriving`	Daily fuel need for driving	Float
`fuelSF`	Safety factor to determine daily fuel need for driving	Float
`parkingDuration`	Number of hours the car is in the neighborhood	Float
`availableHours`	Total hours that the car could be used for vehicle-to-grid, removing the arrival hour and one hour for possible refilling	Float
`durFactor`	Fraction used to calculate the `duration` in VBC contracts	Float
`volFactor`	Fraction used to calculate the `maxVolume` in VBC contracts	Integer
`contract`	Vehicle-to-grid contract that specifies conditions for participation	Object
	Vehicle properties and states	
`countPluginHours`	Cumulative number of plug-in hours	Float
`dailyVolume`	Total daily volume of electricity supplied	Float
`fuelConsumption`	Fuel consumption when driving	Float
`fuelMax`	Maximum hydrogen capacity in vehicle's tank	Float
`hydrogenLevel`	Current level of hydrogen	Float
`usableFuel`	Maximum amount of fuel usable for V2G (`fuelMax` -`minFuelDriving`)	Float
`fuelAvailability`	Current fraction of fuel available for V2G (`hydrogenLevel` -`minFuelDriving`)	Float
`isDriving`	State indicating whether the driver is using the vehicle to drive	Boolean
`isHere`	State indicating whether the driver is in the parking garage	Boolean
`isRefilling`	State indicating whether the driver is using the vehicle to refill	Boolean
`isPluggedin`	State indicating whether the vehicle is plugged in	Boolean
`isV2G`	State indicating whether the vehicle is being used for V2G	Boolean
`isV2G_t`	List of V2G states, where True = 1 and False = 0	Integer (list)
`Hrefill`	Amount of hydrogen refilled in current time step	Float
`pFCEV`	Amount of power being delivered using the vehicle in current time step	Float
`refillCondition`	Factor of available fuel to refill (CBC)	Float
`refillCount`	Total number of refilling instances	Integer
`startUps`	Total number of startUps	Float
`totalHrefill`	Total amount of hydrogen refilled throughout the simulation	Float
`totalPfcev`	Total power being delivered throughout the simulation	Float
	Techno-economic variables of vehicle use	
`CCfcUnit`	Capital cost of fuel cell	Integer
`LTfc`	Lifetime of fuel cell	Integer
`costV2G`	Cost of supplying V2G in current time step	Float
`evalTimer`	Timer for evaluation	Integer
`HrefillCost`	Cost of hydrogen refilled in current time step	Float
`profitV2G`	Profit from V2G supply	Float
`revenuesV2GC`	Capacity revenues in current time step	Float
`revenuesV2GE`	V2G supply revenues in current time step	Float
`revenuesV2G`	Total V2G revenues in current time step	Float
`V2GunitCost`	Cost of producing 1 kWh of electricity using the fuel cell	Float
`avgProfitV2Gdrivers`	Average profit of drivers during evaluation period	Float
`evalCostsV2G`	Total costs of V2G during evaluation period	Float
`evalProfitV2G`	Total profit of V2G during evaluation period	Float
`evalRevenuesC`	Total capacity revenues during evaluation period	Float
`evalRevenuesE`	Total V2G supply revenues during evaluation period	Float
`evalRevenues`	Total V2G revenues during evaluation period	Float
`totalCostsV2G`	Total costs of V2G supply at the end of simulation	Float
`totalProfitV2G`	Total profit from V2G at the end of simulation	Float
`totalRevenuesV2GC`	Total capacity revenues at the end of simulation	Float
`totalRevenuesV2GE`	Total V2G supply revenues at the end of simulation	Float
`totalRevenuesV2G`	Total revenues at the end of simulation	Float

Table A.3: Microgrid objects variables

Variable	Description	Data type
	PV system object	
PVcapacity	PV system capacity	Float
PVpower	Hourly PV generation	Float
PVprofile	Hourly PV capacity factor profile	Float
totalPVpower	Total PV generated	Float
	Wind turbine system object	
windCapacity	Wind turbine capacity	Float
windSpeed	Wind speed in current time step	Float
windPower	Wind generation in current time step	Float
totalWindPower	Total wind power generated	Float
	Electrolyzer-Storage system object	
elecCapacity	Electrolyzer capacity	Float
Hexport	Hourly hydrogen exported	Float
Himport	Hourly hydrogen imported	Float
HSmax	Hydrogen storage capacity	Float
HSmin	Minimum capacity of the hydrogen storage system	Float
HSlevel	Level of hydrogen in the hydrogen storage system	Float
Hrefill	Hourly amount of hydrogen refilled by vehicles	Float
Hproduction	Hourly hydrogen produced	Float
pElec	electrolyzer	Float
totalHexport	Total amount of hydrogen exported	Float
totalHimport	Total amount of hydrogen imported	Float
totalHproduction	Total amount of hydrogen produced in electrolyzer	Float
totalHrefill	Total amount of refilled hydrogen	Float
totalpElec	Level of hydrogen in the hydrogen storage system	Float

Table A.4: VBC-seasonal: Adjusting seasonal contracts

DriverID	Hour time	duration hours	maxVol kWh	minFuel kg	minFuelAvailability
0	0	13	70	3.03	0.53
0	3624	9	50	2.20	0.38
0	5832	13	70	3.03	0.53

Table A.5: CBC-seasonal: Adjusting seasonal contracts

DriverID	Hour time	guarFuel kg	minFuel kg	minFuelAvailability
0	0	0.24	2.94	0.5
0	3624	0.24	2.13	0.35
0	5832	0.24	2.94	0.5

Table A.6: Drivers setup: VBC

		Driver characteristics					V2G contract				
Scenario	`DriverID`	`arrival` Time	`departure`	`availableHours` Hours	`distance` km	`guarFuel` kg	`activation` Time	`duration` Hours	`maxVol` kWh	`minFuel` kg	`minFuelAvailability`
seasonal	0	16	7	13	20	0.12	18	13	70	3.03	0.53
flexible	0	16	9	15	30	0.18	18	13	40	1.84	0.3

Table A.7: Drivers setup: CBC

		Driver characteristics					V2G contract		
Scenario	`DriverID`	`arrival` Time	`departure`	`parkingDuration` Hours	`distance` km	`refillCondition`	`guarFuel` kg	`minFuel` kg	`minfuelAvailability`
seasonal	0	17	11	18	40	0.1	0.24	2.94	0.5
fixed	0	17	9	16	85	0.1	0.51	1.02	0.1

since the electricity consumption of the household agent drives the demand for vehicle-to-grid. Therefore, with two driver agents it is possible to verify the `V2Goperation`, `settle` and `evaluate` methods from the microgrid operator. As a result, changes in state of driver agents caused by such methods can also be verified.

Microgrid operator

V2G operation and Settle The demand for V2G is covered by the two drivers. Taking the first hour of in the VBC-seasonal scenario, we observed how the states of the two driver agents in the model are affected by V2G transaction.Tables A.8 and A.9 show how part of the residual load is covered by the two available FCEVs, and how this affects the electricity price. The costs incurred by the aggregator for the V2G supply is also indicated. Table A.10 shows the corresponding revenues for each of the two drivers, as well as their costs and profit. The total revenues from V2G matches the V2G costs for the aggregator indicated in Table A.9.

Table A.8: Microgrid operator: V2G demand - VBC-flexible scenario

Hour	Load kW	PV kW	ResLoad kW	pImport kW	V2G kW	FCEVsAvailable	FCEVsNeeded	FCEVsUsed
0	95.914	0	95.914	75.914	20	2	10	2

Table A.9: Microgrid operator: Prices, revenues and costs - VBC-flexible scenario

Hour	ElecPricePV €/kWh	ElecPriceV2G €/kWh	ElecPriceImport €/kWh	ElecPrice €/kWh	ElecCostsV2GE €	ElecCostsV2GC €	ElecCostsV2G €
0	0	0.02	0.16	0.18	**2.03**	**0.20**	**2.23**

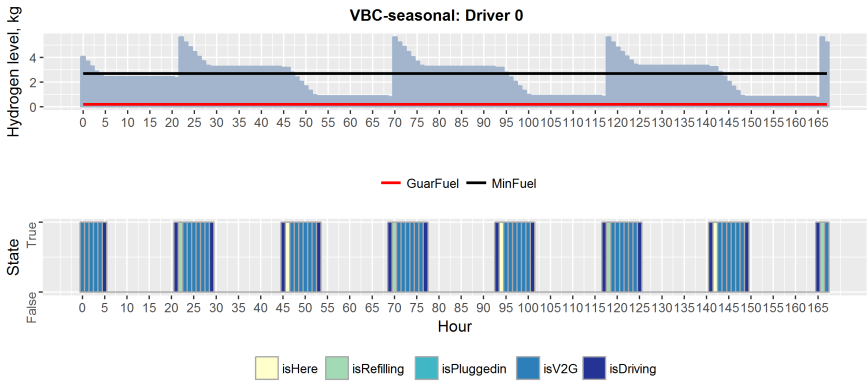
Table A.10: Plugged in drivers: V2G remuneration - VBC-flexible scenario

DriverID	Hour time	pFCEV kW	startups	RevenuesV2GE €	RevenuesV2GC €	RevenuesV2G €	CostV2G €	V2Gprofit €
0	0	10	1	1.01	0.10	1.11	0.97	0.15
1	0	10	1	1.01	0.10	1.11	0.97	0.15
Total		**20**		**2.03**	**0.20**	**2.23**	1.93	0.30

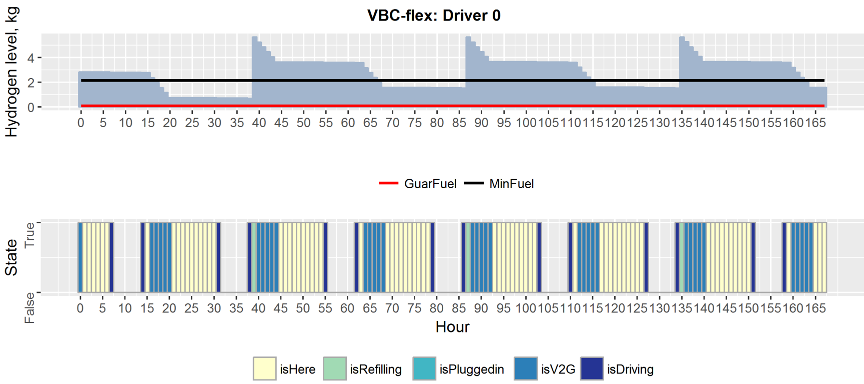
Driver

Drive, refill, plug-in While the driving pattern does not change in the minimal model, the refill and plug-in methods are affected by the existence of household agents. Cars are used for V2G supply and therefore the additional consumption of hydrogen causes the vehicles to refill more frequently. Moreover, even in the VBC contracts where plug-in hours are pre-committed, the plug-in behavior is affected by V2G. If the available fuel for V2G is used up within the plug-in period, cars become unavailable. This is demonstrated in in Fig. A.3 and Fig. A.4.

Adjust Contract In the VBC-flexible contracts, one of the two driver agents can have a higher profit accumulated during the evaluation period. This would make lower earning driver adjust its contract to participate with a higher `duration` or `maxVol`. The

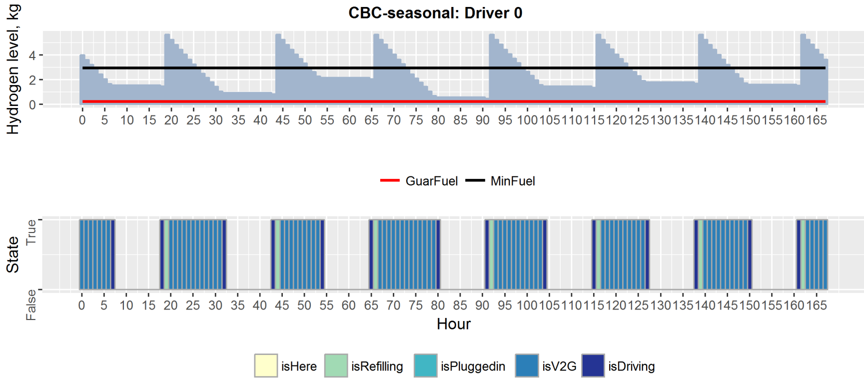


(a) VBC-seasonal

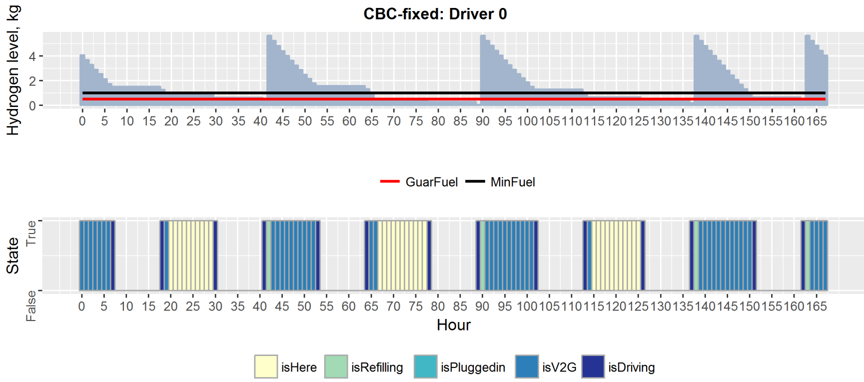


(b) VBC-flexible

Figure A.3: Hydrogen level and states of two FCEVs throughout the first week



(a) CBC-seasonal



(b) CBC-fixed

Figure A.4: Hydrogen level and states of two FCEVs throughout the first week

results show that this occurs as expected (Table A.11). After every evaluation period, the average of the two drivers is calculated and one of the two drivers adjusts the contract accordingly.

Table A.11: VBC-flexible: Adjusting flexible contracts in minimal model

ID	Hour hours	evalProf. €	Avg.[1] €	isAdjustCon.	duration hours	maxVol kWh	minFuel kg	min.[2]
0	0	0.00	0.00	FALSE	9	50	2.14	0.37
0	720	22.13	19.80	FALSE	9	50	2.14	0.37
0	1440	21.97	19.65	FALSE	9	50	2.14	0.37
0	2160	21.95	19.66	FALSE	9	50	2.14	0.37
0	2880	21.90	19.66	FALSE	9	50	2.14	0.37
0	3600	21.87	21.77	FALSE	9	50	2.14	0.37
0	4320	21.88	23.91	TRUE	9	60	2.56	0.45
0	5040	26.36	26.18	FALSE	9	60	2.56	0.45
0	5760	26.22	28.24	TRUE	9	70	2.97	0.52
0	6480	30.80	30.51	FALSE	9	70	2.97	0.52
0	7200	30.70	32.55	TRUE	9	80	3.39	0.6
0	7920	35.12	34.91	FALSE	9	80	3.39	0.6
0	8640	35.17	34.90	FALSE	9	80	3.39	0.6
1	0	0.00	0.00	FALSE	5	40	1.78	0.3
1	720	17.48	19.80	TRUE	6	40	1.78	0.3
1	1440	17.33	19.65	TRUE	7	40	1.78	0.3
1	2160	17.37	19.66	TRUE	8	40	1.78	0.3
1	2880	17.42	19.66	TRUE	8	50	2.20	0.38
1	3600	21.68	21.77	TRUE	8	60	2.62	0.45
1	4320	25.93	23.91	FALSE	8	60	2.62	0.45
1	5040	26.01	26.18	TRUE	8	70	3.03	0.53
1	5760	30.27	28.24	FALSE	8	70	3.03	0.53
1	6480	30.23	30.51	TRUE	8	80	3.45	0.6
1	7200	34.40	32.55	FALSE	8	80	3.45	0.6
1	7920	34.70	34.91	TRUE	8	80	3.45	0.6
1	8640	34.63	34.90	TRUE	8	80	3.45	0.6

Adjust Refill In the CBC-fixed contracts, the average profit is calculated in the same way after the evaluation period. In this case, however, contract parameters are not changed. The *refillCondition* is increased, so that a driver refills more often before plugging in. The results show that one of the drivers has always higher profits (Table A.12). As a result, the refill condition is increased after every evaluation period. This means that in the last month, the driver refills at arrival whenever the *fuelAvailability* is lower or equal to 0.78.

A.3.3. Multi-agent testing

Finally, we run the model 50 driver agents to verify once again the microgrid operator and driver methods.

[1] `AvgProfitEvalDrivers`
[2] `minFuelAvailability`

Table A.12: CBC-fixed: Adjusting refill condition driver with `DriverID` = 9

`DriverID`	Hour hours	`evalProfit` €	`AvgEvalProfitDrivers` €	`isAdjustRefill`	`refillCondition`
0	0	0.00	0.00	FALSE	0.1
0	720	30.13	44.35	TRUE	0.22
0	1440	46.45	52.33	TRUE	0.32
0	2160	47.99	53.21	TRUE	0.41
0	2880	47.86	53.28	TRUE	0.48
0	3600	47.79	52.05	TRUE	0.54
0	4320	47.70	54.00	TRUE	0.59
0	5040	47.82	53.26	TRUE	0.64
0	5760	47.79	53.45	TRUE	0.68
0	6480	47.74	51.07	TRUE	0.71
0	7200	47.76	52.31	TRUE	0.74
0	7920	47.91	54.11	TRUE	0.76
0	8640	47.77	53.04	TRUE	0.78
1	0	0.00	0.00	FALSE	0.1
1	720	58.57	44.35	FALSE	0.1
1	1440	58.21	52.33	FALSE	0.1
1	2160	58.44	53.21	FALSE	0.1
1	2880	58.71	53.28	FALSE	0.1
1	3600	56.32	52.05	FALSE	0.1
1	4320	60.30	54.00	FALSE	0.1
1	5040	58.70	53.26	FALSE	0.1
1	5760	59.11	53.45	FALSE	0.1
1	6480	54.41	51.07	FALSE	0.1
1	7200	56.86	52.31	FALSE	0.1
1	7920	60.32	54.11	FALSE	0.1
1	8640	58.31	53.04	FALSE	0.1

Microgrid operator

Settle To verify the `settle` method, we observe the results at the first hour with solar generation on the second day of the a VBC-flexible scenario simulation. Table A.13 shows the energy balance and demand of V2G in the microgrid, also in the number of vehicles needed. Table A.14 shows the resulting electricity price and costs of V2G - both the energy and the capacity. The corresponding energy and capacity revenues of available FCEVs are listed in Table A.15.

Table A.13: Microgrid operator: V2G demand - VBC-flexible scenario

Hour	`Load` kW	`PV` kW	`ResLoad` kW	`PVtoLoad` kW	`V2G` kW	`FCEVsAvailable`	`FCEVsNeeded`	`FCEVsUsed`
32	85.01	10.63	74.38	10.63	74.38	11	8	8

Table A.14: Microgrid operator: Prices, revenues and costs - VBC-flexible scenario

Hour *Units*	`ElecPricePV` €/kWh	`ElecPriceV2G` €/kWh	`ElecPrice` €/kWh	`ElecCostsV2GE` €	`ElecCostsV2GC` €	`ElecCostsV2G` €
32	0.0070	0.0888	0.0958	7.55	1.10	8.65

Evaluate To verify the microgrid operator's *evaluate* method we observe the drivers' profits after the first evaluation, in the CBC-fixed scenario. The average profit of drivers

Table A.15: Plugged in drivers: V2G remuneration - VBC-flexible scenario

DriverID	Hour time	pFCEV kW	startups	RevenuesV2GE €	RevenuesV2GC €	RevenuesV2G €	CostV2G €	V2Gprofit €
5	32	0.00	2	0.0000	0.1000	0.1000	0.0000	0.1000
16	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
18	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
22	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
25	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
26	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
31	32	9.30	2	0.9432	0.1000	1.0432	0.8983	0.1449
33	32	0.00	1	0.0000	0.1000	0.1000	0.0000	0.1000
37	32	9.30	1	0.9432	0.1000	1.0432	0.8983	0.1449
42	32	9.30	1	0.9432	0.1000	1.0432	0.8983	0.1449
45	32	0.00	1	0.0000	0.1000	0.1000	0.0000	0.1000
	Total	**74.38**		**7.55**	**1.10**	**8.65**	**7.19**	**1.46**

indicated in Table A.16 is a number communicated from the microgrid operator to the drivers.

Driver Make Contract Table A.17 shows the drivers' setup in the VBC-seasonal implementation. As expected, the `duration` matches the `availableHours`, since maximum availability is required in winter. Table A.18 shows, on the other hand, that the contracted duration does not always match the maximum available hours. Table A.19 and Table A.20 show the differences in control-based contract implementations. While in the first one a minimum fuel availability (for plug-in) of 0.5 is seen for all drivers, this value is 0.1 in the CBC-fixed implementation.

Table A.16: Evaluation: Drivers Average Profits

DriverID	Hour Units	EvalProfit €	AvgEvalProfitDrivers €
0	720	50.64	42.77
1	720	50.83	42.77
2	720	49.48	42.77
3	720	66.86	42.77
4	720	37.24	42.77
5	720	35.16	42.77
6	720	51.24	42.77
7	720	43.83	42.77
8	720	48.88	42.77
9	720	37.42	42.77
10	720	55.37	42.77
11	720	33.59	42.77
12	720	17.14	42.77
13	720	12.42	42.77
14	720	38.89	42.77
15	720	48.73	42.77
16	720	40.57	42.77
17	720	24.91	42.77
18	720	49.45	42.77
19	720	30.14	42.77
20	720	39.03	42.77
21	720	33.56	42.77
22	720	56.59	42.77
23	720	40.95	42.77
24	720	41.29	42.77
25	720	50.74	42.77
26	720	36.42	42.77
27	720	30.45	42.77
28	720	66.54	42.77
29	720	56.14	42.77
30	720	37.49	42.77
31	720	31.78	42.77
32	720	37.10	42.77
33	720	19.19	42.77
34	720	47.82	42.77
35	720	36.46	42.77
36	720	42.43	42.77
37	720	45.19	42.77
38	720	59.25	42.77
39	720	60.10	42.77
40	720	22.00	42.77
41	720	61.59	42.77
42	720	27.74	42.77
43	720	38.50	42.77
44	720	56.83	42.77
45	720	49.03	42.77
46	720	57.18	42.77
47	720	37.84	42.77
48	720	57.03	42.77
49	720	39.42	42.77

Table A.17: Drivers setup: VBC-seasonal

	Driver characteristics					V2G contract						
DriverID	arrival	departure Time	availableHours Hours	distance km	guarFuel kg	activation Time	duration Hours	maxVol kWh	minFuel kg	energyRem. €/kWh	capacityRem. €/kW-h	minfuelAvailability
0	12	9	19	25	0.15	14	19	70	3.06	0.10144	0.01	0.53
1	16	5	11	110	0.66	18	11	60	3.16	0.10144	0.01	0.5
2	16	7	13	110	0.66	18	13	60	3.16	0.10144	0.01	0.5
3	12	9	19	55	0.33	14	19	60	2.83	0.10144	0.01	0.47
4	15	9	16	25	0.15	17	16	70	3.06	0.10144	0.01	0.53
5	17	13	18	80	0.48	19	18	60	2.98	0.10144	0.01	0.48
6	23	8	7	110	0.66	1	7	60	3.16	0.10144	0.01	0.5
7	19	7	10	65	0.39	21	10	60	2.89	0.10144	0.01	0.48
8	15	6	13	110	0.66	17	13	60	3.16	0.10144	0.01	0.5
9	12	5	15	10	0.06	14	15	70	2.97	0.10144	0.01	0.52
10	20	8	10	95	0.57	22	10	60	3.07	0.10144	0.01	0.49
11	19	8	11	110	0.66	21	11	60	3.16	0.10144	0.01	0.5
12	17	7	12	110	0.66	19	12	60	3.16	0.10144	0.01	0.5
13	23	7	6	60	0.36	1	6	60	2.86	0.10144	0.01	0.47
14	23	11	10	10	0.06	1	10	70	2.97	0.10144	0.01	0.52
15	12	8	18	110	0.66	14	18	60	3.16	0.10144	0.01	0.5
16	21	9	10	10	0.06	23	10	70	2.97	0.10144	0.01	0.52
17	21	6	7	20	0.12	23	7	70	3.03	0.10144	0.01	0.53
18	17	16	21	110	0.66	19	21	60	3.16	0.10144	0.01	0.5
19	13	7	16	20	0.12	15	16	70	3.03	0.10144	0.01	0.53
20	13	10	19	60	0.36	15	19	60	2.86	0.10144	0.01	0.47
21	18	8	12	15	0.09	20	12	70	3.00	0.10144	0.01	0.52
22	17	13	18	55	0.33	19	18	60	2.83	0.10144	0.01	0.47
23	21	6	7	110	0.66	23	7	60	3.16	0.10144	0.01	0.5
24	21	8	9	55	0.33	23	9	60	2.83	0.10144	0.01	0.47
25	15	10	17	75	0.45	17	17	60	2.95	0.10144	0.01	0.48
26	19	9	12	20	0.12	21	12	70	3.03	0.10144	0.01	0.53
27	13	7	16	25	0.15	15	16	70	3.06	0.10144	0.01	0.53
28	12	7	17	90	0.54	14	17	60	3.04	0.10144	0.01	0.49
29	19	7	10	5	0.03	21	10	70	2.94	0.10144	0.01	0.52
30	19	8	11	60	0.36	21	11	60	2.86	0.10144	0.01	0.47
31	17	14	19	45	0.27	19	19	60	2.77	0.10144	0.01	0.46
32	18	6	10	30	0.18	20	10	70	3.09	0.10144	0.01	0.53
33	17	12	17	10	0.06	19	17	70	2.97	0.10144	0.01	0.52
34	17	8	13	45	0.27	19	13	60	2.77	0.10144	0.01	0.46
35	8	5	19	20	0.12	10	19	70	3.03	0.10144	0.01	0.53
36	20	7	9	110	0.66	22	9	60	3.16	0.10144	0.01	0.5
37	21	10	11	110	0.66	23	11	60	3.16	0.10144	0.01	0.5
38	14	10	18	15	0.09	16	18	70	3.00	0.10144	0.01	0.52
39	18	5	9	50	0.30	20	9	60	2.80	0.10144	0.01	0.47
40	16	9	15	10	0.06	18	15	70	2.97	0.10144	0.01	0.52
41	23	8	7	20	0.12	1	7	70	3.03	0.10144	0.01	0.53
42	23	10	9	10	0.06	1	9	70	2.97	0.10144	0.01	0.52
43	14	8	16	25	0.15	16	16	70	3.06	0.10144	0.01	0.53
44	19	6	9	30	0.18	21	9	70	3.09	0.10144	0.01	0.53
45	18	15	19	25	0.15	20	19	70	3.06	0.10144	0.01	0.53
46	11	9	20	5	0.03	13	20	70	2.94	0.10144	0.01	0.52
47	16	6	12	40	0.24	18	12	60	2.74	0.10144	0.01	0.46
48	14	8	16	15	0.09	16	16	70	3.00	0.10144	0.01	0.52
49	17	8	13	15	0.09	19	13	70	3.00	0.10144	0.01	0.52

Table A.18: Drivers setup: VBC-flexible

	Driver characteristics				V2G contract							
DriverID	arrival	departure	availableHours	distance	minFuelDriving	activation	duration	maxVol	minFuel	energyRem.	capacityRem.	minfuelAvailability
	Time		Hours	km	kg	Time	Hours	kWh	kg	€/kWh	€/kW-h	
0	16	7	13	30	0.18	18	12	60	2.68	0.10144	0.01	0.46
1	15	7	14	80	0.48	17	9	40	2.15	0.10144	0.01	0.32
2	13	7	16	10	0.06	15	16	40	1.72	0.10144	0.01	0.3
3	22	7	7	40	0.24	0	4	40	1.90	0.10144	0.01	0.31
4	17	10	15	50	0.30	19	12	30	1.55	0.10144	0.01	0.23
5	16	11	17	70	0.42	18	10	40	2.09	0.10144	0.01	0.32
6	17	7	12	40	0.24	19	10	40	1.90	0.10144	0.01	0.31
7	13	9	18	55	0.33	15	14	40	2.00	0.10144	0.01	0.31
8	13	11	20	55	0.33	15	10	60	2.83	0.10144	0.01	0.47
9	20	6	8	85	0.51	22	7	50	2.59	0.10144	0.01	0.41
10	12	7	17	110	0.66	14	16	60	3.16	0.10144	0.01	0.5
11	16	9	15	20	0.12	18	8	40	1.78	0.10144	0.01	0.3
12	17	11	16	110	0.66	19	12	50	2.74	0.10144	0.01	0.42
13	13	12	21	110	0.66	15	11	40	2.33	0.10144	0.01	0.33
14	18	14	18	100	0.60	20	12	40	2.27	0.10144	0.01	0.33
15	17	7	12	20	0.12	19	12	40	1.78	0.10144	0.01	0.3
16	17	6	11	30	0.18	19	7	60	2.68	0.10144	0.01	0.46
17	19	12	15	110	0.66	21	14	60	3.16	0.10144	0.01	0.5
18	15	9	16	15	0.09	17	12	50	2.17	0.10144	0.01	0.37
19	18	14	18	30	0.18	20	12	50	2.26	0.10144	0.01	0.38
20	23	8	7	60	0.36	1	6	60	2.86	0.10144	0.01	0.47
21	13	5	14	30	0.18	15	10	50	2.26	0.10144	0.01	0.38
22	22	8	8	15	0.09	0	8	50	2.17	0.10144	0.01	0.37
23	16	7	13	5	0.03	18	12	60	2.53	0.10144	0.01	0.44
24	14	10	18	60	0.36	16	17	60	2.86	0.10144	0.01	0.47
25	20	16	18	70	0.42	22	15	40	2.09	0.10144	0.01	0.32
26	10	6	18	55	0.33	12	10	60	2.83	0.10144	0.01	0.47
27	16	6	12	110	0.66	18	11	40	2.33	0.10144	0.01	0.33
28	19	9	12	30	0.18	21	11	50	2.26	0.10144	0.01	0.38
29	17	9	14	35	0.21	19	11	40	1.87	0.10144	0.01	0.31
30	15	8	15	80	0.48	17	9	40	2.15	0.10144	0.01	0.32
31	14	11	19	10	0.06	16	16	60	2.56	0.10144	0.01	0.45
32	21	11	12	20	0.12	23	9	60	2.62	0.10144	0.01	0.45
33	13	6	15	15	0.09	15	11	40	1.75	0.10144	0.01	0.3
34	20	8	10	20	0.12	22	6	60	2.62	0.10144	0.01	0.45
35	14	6	14	25	0.15	16	11	70	3.06	0.10144	0.01	0.53
36	17	9	14	25	0.15	19	10	60	2.65	0.10144	0.01	0.45
37	14	7	15	35	0.21	16	14	60	2.71	0.10144	0.01	0.46
38	20	11	13	5	0.03	22	11	60	2.53	0.10144	0.01	0.44
39	19	13	16	20	0.12	21	11	40	1.78	0.10144	0.01	0.3
40	17	13	18	10	0.06	19	13	60	2.56	0.10144	0.01	0.45
41	13	12	21	25	0.15	15	18	40	1.81	0.10144	0.01	0.3
42	17	7	12	35	0.21	19	9	40	1.87	0.10144	0.01	0.31
43	16	8	14	55	0.33	18	11	40	2.00	0.10144	0.01	0.31
44	12	11	21	30	0.18	14	14	40	1.84	0.10144	0.01	0.3
45	21	9	10	40	0.24	23	8	30	1.49	0.10144	0.01	0.23
46	15	8	15	110	0.66	17	11	50	2.74	0.10144	0.01	0.42
47	23	11	10	5	0.03	1	8	50	2.11	0.10144	0.01	0.37
48	11	10	21	110	0.66	13	18	50	2.74	0.10144	0.01	0.42
49	17	11	16	110	0.66	19	14	30	1.91	0.10144	0.01	0.25

Table A.19: Drivers setup: CBC-seasonal

Driver characteristics					V2G contract				
DriverID	Arrival Time	Departure	parkingDuration Hours	distance km	guarFuel kg	minFuel kg	energyRem. €/kWh	capacityRem. €/kW-h	minfuelAvailability
0	15	6	15	110	0.66	3.15	0.10144	0.01	0.5
1	16	7	15	40	0.24	2.94	0.10144	0.01	0.5
2	16	6	14	5	0.03	2.84	0.10144	0.01	0.5
3	17	16	23	70	0.42	3.03	0.10144	0.01	0.5
4	18	9	15	30	0.18	2.91	0.10144	0.01	0.5
5	18	13	19	65	0.39	3.02	0.10144	0.01	0.5
6	20	8	12	15	0.09	2.87	0.10144	0.01	0.5
7	12	7	19	20	0.12	2.88	0.10144	0.01	0.5
8	13	8	19	30	0.18	2.91	0.10144	0.01	0.5
9	21	8	11	90	0.54	3.09	0.10144	0.01	0.5
10	17	8	15	15	0.09	2.87	0.10144	0.01	0.5
11	17	5	12	15	0.09	2.87	0.10144	0.01	0.5
12	11	8	21	40	0.24	2.94	0.10144	0.01	0.5
13	17	15	22	110	0.66	3.15	0.10144	0.01	0.5
14	18	11	17	75	0.45	3.05	0.10144	0.01	0.5
15	15	5	14	25	0.15	2.9	0.10144	0.01	0.5
16	17	9	16	15	0.09	2.87	0.10144	0.01	0.5
17	16	11	19	60	0.36	3	0.10144	0.01	0.5
18	17	8	15	10	0.06	2.85	0.10144	0.01	0.5
19	17	4	11	50	0.30	2.97	0.10144	0.01	0.5
20	20	6	10	15	0.09	2.87	0.10144	0.01	0.5
21	19	9	14	25	0.15	2.9	0.10144	0.01	0.5
22	22	10	12	90	0.54	3.09	0.10144	0.01	0.5
23	19	12	17	55	0.33	2.99	0.10144	0.01	0.5
24	16	8	16	35	0.21	2.93	0.10144	0.01	0.5
25	20	8	12	35	0.21	2.93	0.10144	0.01	0.5
26	17	9	16	40	0.24	2.94	0.10144	0.01	0.5
27	23	8	9	10	0.06	2.85	0.10144	0.01	0.5
28	15	9	18	20	0.12	2.88	0.10144	0.01	0.5
29	14	12	22	10	0.06	2.85	0.10144	0.01	0.5
30	19	8	13	10	0.06	2.85	0.10144	0.01	0.5
31	21	7	10	20	0.12	2.88	0.10144	0.01	0.5
32	23	6	7	30	0.18	2.91	0.10144	0.01	0.5
33	11	8	21	45	0.27	2.96	0.10144	0.01	0.5
34	17	11	18	40	0.24	2.94	0.10144	0.01	0.5
35	11	6	19	40	0.24	2.94	0.10144	0.01	0.5
36	21	6	9	65	0.39	3.02	0.10144	0.01	0.5
37	17	14	21	70	0.42	3.03	0.10144	0.01	0.5
38	17	14	21	105	0.63	3.14	0.10144	0.01	0.5
39	14	11	21	30	0.18	2.91	0.10144	0.01	0.5
40	18	8	14	110	0.66	3.15	0.10144	0.01	0.5
41	12	6	18	110	0.66	3.15	0.10144	0.01	0.5
42	18	9	15	10	0.06	2.85	0.10144	0.01	0.5
43	17	10	17	110	0.66	3.15	0.10144	0.01	0.5
44	22	5	7	110	0.66	3.15	0.10144	0.01	0.5
45	14	10	20	10	0.06	2.85	0.10144	0.01	0.5
46	13	10	21	45	0.27	2.96	0.10144	0.01	0.5
47	15	8	17	30	0.18	2.91	0.10144	0.01	0.5
48	17	6	13	95	0.57	3.11	0.10144	0.01	0.5
49	17	7	14	25	0.1506	2.9	0.10144	0.01	0.5

Table A.20: Drivers setup: CBC-fixed

Driver characteristics						V2G contract				
DriverID	Arrival Time	Departure	parkingDuration Hours	distance km	refillCondition	guarFuel kg	minFuel kg	energyRem. €/kWh	capacityRem. €/kW-h	minfuelAvailability
0	17	11	18	110	0.1	0.66	1.16	0.10144	0.01	0.1
1	15	11	20	45	0.1	0.27	0.81	0.10144	0.01	0.1
2	14	11	21	50	0.1	0.30	0.84	0.10144	0.01	0.1
3	16	15	23	45	0.1	0.27	0.81	0.10144	0.01	0.1
4	19	8	13	95	0.1	0.57	1.08	0.10144	0.01	0.1
5	22	11	13	10	0.1	0.06	0.62	0.10144	0.01	0.1
6	15	11	20	110	0.1	0.66	1.16	0.10144	0.01	0.1
7	12	7	19	110	0.1	0.66	1.16	0.10144	0.01	0.1
8	14	10	20	100	0.1	0.60	1.11	0.10144	0.01	0.1
9	15	6	15	50	0.1	0.30	0.84	0.10144	0.01	0.1
10	19	14	19	25	0.1	0.15	0.7	0.10144	0.01	0.1
11	16	5	13	65	0.1	0.39	0.92	0.10144	0.01	0.1
12	23	8	9	40	0.1	0.24	0.78	0.10144	0.01	0.1
13	23	8	9	10	0.1	0.06	0.62	0.10144	0.01	0.1
14	17	8	15	85	0.1	0.51	1.02	0.10144	0.01	0.1
15	10	8	22	40	0.1	0.24	0.78	0.10144	0.01	0.1
16	20	10	14	40	0.1	0.24	0.78	0.10144	0.01	0.1
17	21	6	9	20	0.1	0.12	0.67	0.10144	0.01	0.1
18	12	8	20	110	0.1	0.66	1.16	0.10144	0.01	0.1
19	19	6	11	50	0.1	0.30	0.84	0.10144	0.01	0.1
20	16	8	16	75	0.1	0.45	0.97	0.10144	0.01	0.1
21	19	7	12	5	0.1	0.03	0.59	0.10144	0.01	0.1
22	14	12	22	40	0.1	0.24	0.78	0.10144	0.01	0.1
23	14	6	16	5	0.1	0.03	0.59	0.10144	0.01	0.1
24	16	8	16	10	0.1	0.06	0.62	0.10144	0.01	0.1
25	21	14	17	20	0.1	0.12	0.67	0.10144	0.01	0.1
26	22	11	13	55	0.1	0.33	0.86	0.10144	0.01	0.1
27	20	7	11	15	0.1	0.09	0.65	0.10144	0.01	0.1
28	19	17	22	10	0.1	0.06	0.62	0.10144	0.01	0.1
29	19	14	19	5	0.1	0.03	0.59	0.10144	0.01	0.1
30	19	8	13	5	0.1	0.03	0.59	0.10144	0.01	0.1
31	20	7	11	15	0.1	0.09	0.65	0.10144	0.01	0.1
32	19	8	13	40	0.1	0.24	0.78	0.10144	0.01	0.1
33	23	10	11	105	0.1	0.63	1.13	0.10144	0.01	0.1
34	12	8	20	55	0.1	0.33	0.86	0.10144	0.01	0.1
35	19	8	13	110	0.1	0.66	1.16	0.10144	0.01	0.1
36	15	6	15	55	0.1	0.33	0.86	0.10144	0.01	0.1
37	16	8	16	50	0.1	0.30	0.84	0.10144	0.01	0.1
38	8	3	19	105	0.1	0.63	1.13	0.10144	0.01	0.1
39	13	11	22	10	0.1	0.06	0.62	0.10144	0.01	0.1
40	23	12	13	10	0.1	0.06	0.62	0.10144	0.01	0.1
41	10	9	23	20	0.1	0.12	0.67	0.10144	0.01	0.1
42	21	7	10	40	0.1	0.24	0.78	0.10144	0.01	0.1
43	18	8	14	70	0.1	0.42	0.94	0.10144	0.01	0.1
44	12	6	18	50	0.1	0.30	0.84	0.10144	0.01	0.1
45	16	8	16	70	0.1	0.42	0.94	0.10144	0.01	0.1
46	17	13	20	15	0.1	0.09	0.65	0.10144	0.01	0.1
47	21	10	13	10	0.1	0.06	0.62	0.10144	0.01	0.1
48	15	13	22	30	0.1	0.18	0.73	0.10144	0.01	0.1
49	17	8	15	105	0.1	0.63	1.13	0.10144	0.01	0.1

Drive, refill, plug-in The drivers' daily actions can be observed following the change in state (drive, refill, plug-in, V2G) and the level of hydrogen in the tank.

In volume-based scenarios, the driving occurs at the same time every day. The plug-in hours are also fixed. The refilling occurs before plugging in, when necessary. Figure A.5 shows the hydrogen level and the states of two driver agents with similar driving needs throughout the first week.

In control-based scenarios, the driving occurs around the same time every day, with a +-1 hour variation. The plug-in hours are defined by the fuel available and the hours of parking. The refilling occurs before plugging in, when necessary. Figure A.6 shows the hydrogen level and the states of two driver agents with similar driving needs throughout the first week.

Adjust Seasonal Contract Tables A.21 and A.22 show how the initial contract parameters are reduced by 70% in the summer months, and restore to the initial values at the beginning of September.

Table A.21: VBC-seasonal: Adjusting seasonal contracts

DriverID	Hour	duration	maxVol	minFuel	CFuelAvailability
0	0	19	70	3.06	0.53
0	3624	13	50	2.23	0.38
0	5832	19	70	3.06	0.53
1	0	11	60	3.16	0.5
1	3624	8	40	2.33	0.33
1	5832	11	60	3.16	0.5
2	0	13	60	3.16	0.5
2	3624	9	40	2.33	0.33
2	5832	13	60	3.16	0.5
3	0	19	60	2.83	0.47
3	3624	13	40	2.00	0.31
3	5832	19	60	2.83	0.47
4	0	16	70	3.06	0.53
4	3624	11	50	2.23	0.38
4	5832	16	70	3.06	0.53
5	0	18	60	2.98	0.48
5	3624	13	40	2.15	0.32
5	5832	18	60	2.98	0.48
6	0	7	60	3.16	0.5
6	3624	5	40	2.33	0.33
6	5832	7	60	3.16	0.5
7	0	10	60	2.89	0.48
7	3624	7	40	2.06	0.32
7	5832	10	60	2.89	0.48
8	0	13	60	3.16	0.5
8	3624	9	40	2.33	0.33
8	5832	13	60	3.16	0.5
9	0	15	70	2.97	0.52
9	3624	10	50	2.14	0.37
9	5832	15	70	2.97	0.52
10	0	10	60	3.07	0.49
10	3624	7	40	2.24	0.33
10	5832	10	60	3.07	0.49
11	0	11	60	3.16	0.5
11	3624	8	40	2.33	0.33
11	5832	11	60	3.16	0.5
12	0	12	60	3.16	0.5
12	3624	8	40	2.33	0.33
12	5832	12	60	3.16	0.5
13	0	6	60	2.86	0.47

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TableA.21 – *Continued*

DriverID	Hour	duration	maxVol	minFuel	CFuelAvailability
13	3624	4	40	2.03	0.32
13	5832	6	60	2.86	0.47
14	0	10	70	2.97	0.52
14	3624	7	50	2.14	0.37
14	5832	10	70	2.97	0.52
15	0	18	60	3.16	0.5
15	3624	13	40	2.33	0.33
15	5832	18	60	3.16	0.5
16	0	10	70	2.97	0.52
16	3624	7	50	2.14	0.37
16	5832	10	70	2.97	0.52
17	0	7	70	3.03	0.53
17	3624	5	50	2.20	0.38
17	5832	7	70	3.03	0.53
18	0	21	60	3.16	0.5
18	3624	15	40	2.33	0.33
18	5832	21	60	3.16	0.5
19	0	16	70	3.03	0.53
19	3624	11	50	2.20	0.38
19	5832	16	70	3.03	0.53
20	0	19	60	2.86	0.47
20	3624	13	40	2.03	0.32
20	5832	19	60	2.86	0.47
21	0	12	70	3.00	0.52
21	3624	8	50	2.17	0.37
21	5832	12	70	3.00	0.52
22	0	18	60	2.83	0.47
22	3624	13	40	2.00	0.31
22	5832	18	60	2.83	0.47
23	0	7	60	3.16	0.5
23	3624	5	40	2.33	0.33
23	5832	7	60	3.16	0.5
24	0	9	60	2.83	0.47
24	3624	6	40	2.00	0.31
24	5832	9	60	2.83	0.47
25	0	17	60	2.95	0.48
25	3624	12	40	2.12	0.32
25	5832	17	60	2.95	0.48
26	0	12	70	3.03	0.53
26	3624	8	50	2.20	0.38
26	5832	12	70	3.03	0.53
27	0	16	70	3.06	0.53
27	3624	11	50	2.23	0.38
27	5832	16	70	3.06	0.53
28	0	17	60	3.04	0.49
28	3624	12	40	2.21	0.33
28	5832	17	60	3.04	0.49
29	0	10	70	2.94	0.52
29	3624	7	50	2.11	0.37
29	5832	10	70	2.94	0.52
30	0	11	60	2.86	0.47
30	3624	8	40	2.03	0.32
30	5832	11	60	2.86	0.47
31	0	19	60	2.77	0.46
31	3624	13	40	1.93	0.31
31	5832	19	60	2.77	0.46
32	0	10	70	3.09	0.53
32	3624	7	50	2.26	0.38
32	5832	10	70	3.09	0.53
33	0	17	70	2.97	0.52
33	3624	12	50	2.14	0.37
33	5832	17	70	2.97	0.52
34	0	13	60	2.77	0.46
34	3624	9	40	1.93	0.31
34	5832	13	60	2.77	0.46

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TableA.21 – *Continued*

DriverID	Hour	duration	maxVol	minFuel	CFuelAvailability
35	0	19	70	3.03	0.53
35	3624	13	50	2.20	0.38
35	5832	19	70	3.03	0.53
36	0	9	60	3.16	0.5
36	3624	6	40	2.33	0.33
36	5832	9	60	3.16	0.5
37	0	11	60	3.16	0.5
37	3624	8	40	2.33	0.33
37	5832	11	60	3.16	0.5
38	0	18	70	3.00	0.52
38	3624	13	50	2.17	0.37
38	5832	18	70	3.00	0.52
39	0	9	60	2.80	0.47
39	3624	6	40	1.97	0.31
39	5832	9	60	2.80	0.47
40	0	15	70	2.97	0.52
40	3624	10	50	2.14	0.37
40	5832	15	70	2.97	0.52
41	0	7	70	3.03	0.53
41	3624	5	50	2.20	0.38
41	5832	7	70	3.03	0.53
42	0	9	70	2.97	0.52
42	3624	6	50	2.14	0.37
42	5832	9	70	2.97	0.52
43	0	16	70	3.06	0.53
43	3624	11	50	2.23	0.38
43	5832	16	70	3.06	0.53
44	0	9	70	3.09	0.53
44	3624	6	50	2.26	0.38
44	5832	9	70	3.09	0.53
45	0	19	70	3.06	0.53
45	3624	13	50	2.23	0.38
45	5832	19	70	3.06	0.53
46	0	20	70	2.94	0.52
46	3624	14	50	2.11	0.37
46	5832	20	70	2.94	0.52
47	0	12	60	2.74	0.46
47	3624	8	40	1.90	0.31
47	5832	12	60	2.74	0.46
48	0	16	70	3.00	0.52
48	3624	11	50	2.17	0.37
48	5832	16	70	3.00	0.52
49	0	13	70	3.00	0.52
49	3624	9	50	2.17	0.37
49	5832	13	70	3.00	0.52

Table A.22: CBC-seasonal: Adjusting seasonal contracts

DriverID	Hour	guarFuel	minFuel	CFuelAvailability
0	0	0.66	3.15	0.5
0	3624	0.66	2.4	0.35
0	5832	0.66	3.15	0.5
1	0	0.24	2.94	0.5
1	3624	0.24	2.13	0.35
1	5832	0.24	2.94	0.5
2	0	0.03	2.84	0.5
2	3624	0.03	1.99	0.35
2	5832	0.03	2.84	0.5
3	0	0.42	3.03	0.5
3	3624	0.42	2.25	0.35
3	5832	0.42	3.03	0.5
4	0	0.18	2.91	0.5
4	3624	0.18	2.09	0.35

Continued on next page

TableA.22 – *Continued*

DriverID	Hour	guarFuel	minFuel	CFuelAvailability
4	5832	0.18	2.91	0.5
5	0	0.39	3.02	0.5
5	3624	0.39	2.23	0.35
5	5832	0.39	3.02	0.5
6	0	0.09	2.87	0.5
6	3624	0.09	2.03	0.35
6	5832	0.09	2.87	0.5
7	0	0.12	2.88	0.5
7	3624	0.12	2.05	0.35
7	5832	0.12	2.88	0.5
8	0	0.18	2.91	0.5
8	3624	0.18	2.09	0.35
8	5832	0.18	2.91	0.5
9	0	0.54	3.09	0.5
9	3624	0.54	2.33	0.35
9	5832	0.54	3.09	0.5
10	0	0.09	2.87	0.5
10	3624	0.09	2.03	0.35
10	5832	0.09	2.87	0.5
11	0	0.09	2.87	0.5
11	3624	0.09	2.03	0.35
11	5832	0.09	2.87	0.5
12	0	0.24	2.94	0.5
12	3624	0.24	2.13	0.35
12	5832	0.24	2.94	0.5
13	0	0.66	3.15	0.5
13	3624	0.66	2.4	0.35
13	5832	0.66	3.15	0.5
14	0	0.45	3.05	0.5
14	3624	0.45	2.27	0.35
14	5832	0.45	3.05	0.5
15	0	0.15	2.9	0.5
15	3624	0.15	2.07	0.35
15	5832	0.15	2.9	0.5
16	0	0.09	2.87	0.5
16	3624	0.09	2.03	0.35
16	5832	0.09	2.87	0.5
17	0	0.36	3	0.5
17	3624	0.36	2.21	0.35
17	5832	0.36	3	0.5
18	0	0.06	2.85	0.5
18	3624	0.06	2.01	0.35
18	5832	0.06	2.85	0.5
19	0	0.30	2.97	0.5
19	3624	0.30	2.17	0.35
19	5832	0.30	2.97	0.5
20	0	0.09	2.87	0.5
20	3624	0.09	2.03	0.35
20	5832	0.09	2.87	0.5
21	0	0.15	2.9	0.5
21	3624	0.15	2.07	0.35
21	5832	0.15	2.9	0.5
22	0	0.54	3.09	0.5
22	3624	0.54	2.33	0.35
22	5832	0.54	3.09	0.5
23	0	0.33	2.99	0.5
23	3624	0.33	2.19	0.35
23	5832	0.33	2.99	0.5
24	0	0.21	2.93	0.5
24	3624	0.21	2.11	0.35
24	5832	0.21	2.93	0.5
25	0	0.21	2.93	0.5
25	3624	0.21	2.11	0.35
25	5832	0.21	2.93	0.5
26	0	0.24	2.94	0.5

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TableA.22 – *Continued*

DriverID	Hour	guarFuel	minFuel	CFuelAvailability
26	3624	0.24	2.13	0.35
26	5832	0.24	2.94	0.5
27	0	0.06	2.85	0.5
27	3624	0.06	2.01	0.35
27	5832	0.06	2.85	0.5
28	0	0.12	2.88	0.5
28	3624	0.12	2.05	0.35
28	5832	0.12	2.88	0.5
29	0	0.06	2.85	0.5
29	3624	0.06	2.01	0.35
29	5832	0.06	2.85	0.5
30	0	0.06	2.85	0.5
30	3624	0.06	2.01	0.35
30	5832	0.06	2.85	0.5
31	0	0.12	2.88	0.5
31	3624	0.12	2.05	0.35
31	5832	0.12	2.88	0.5
32	0	0.18	2.91	0.5
32	3624	0.18	2.09	0.35
32	5832	0.18	2.91	0.5
33	0	0.27	2.96	0.5
33	3624	0.27	2.15	0.35
33	5832	0.27	2.96	0.5
34	0	0.24	2.94	0.5
34	3624	0.24	2.13	0.35
34	5832	0.24	2.94	0.5
35	0	0.24	2.94	0.5
35	3624	0.24	2.13	0.35
35	5832	0.24	2.94	0.5
36	0	0.39	3.02	0.5
36	3624	0.39	2.23	0.35
36	5832	0.39	3.02	0.5
37	0	0.42	3.03	0.5
37	3624	0.42	2.25	0.35
37	5832	0.42	3.03	0.5
38	0	0.63	3.14	0.5
38	3624	0.63	2.39	0.35
38	5832	0.63	3.14	0.5
39	0	0.18	2.91	0.5
39	3624	0.18	2.09	0.35
39	5832	0.18	2.91	0.5
40	0	0.66	3.15	0.5
40	3624	0.66	2.4	0.35
40	5832	0.66	3.15	0.5
41	0	0.66	3.15	0.5
41	3624	0.66	2.4	0.35
41	5832	0.66	3.15	0.5
42	0	0.06	2.85	0.5
42	3624	0.06	2.01	0.35
42	5832	0.06	2.85	0.5
43	0	0.66	3.15	0.5
43	3624	0.66	2.4	0.35
43	5832	0.66	3.15	0.5
44	0	0.66	3.15	0.5
44	3624	0.66	2.4	0.35
44	5832	0.66	3.15	0.5
45	0	0.06	2.85	0.5
45	3624	0.06	2.01	0.35
45	5832	0.06	2.85	0.5
46	0	0.27	2.96	0.5
46	3624	0.27	2.15	0.35
46	5832	0.27	2.96	0.5
47	0	0.18	2.91	0.5
47	3624	0.18	2.09	0.35
47	5832	0.18	2.91	0.5

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TableA.22 – *Continued*

DriverID	Hour	guarFuel	minFuel	CFuelAvailability
48	0	0.57	3.11	0.5
48	3624	0.57	2.35	0.35
48	5832	0.57	3.11	0.5
49	0	0.15	2.9	0.5
49	3624	0.15	2.07	0.35
49	5832	0.15	2.9	0.5

Adjust flexible contract The contract parameters can be updated by drivers in the VBC-flexible scenario. Table A.23 shows the change in parameters of one driver agent. It shows how either the `maxVolume` or `duration` are increased when its profit is lower than the average profit of all drivers, following eq. 6.7 and 6.6.

Table A.23: VBC-flexible: Adjusting flexible contracts, driver with `DriverID` = 0

Hour time	evalProfit €	AvgEvalProfitDrivers €	isAdjustContract	duration hours	maxVol kWh	minFuel kg	minFuelAvailability
720	33.59	27.81	FALSE	12	60	2.68	0.46
1440	34.16	30.49	FALSE	12	60	2.68	0.46
2160	33.39	31.69	FALSE	12	60	2.68	0.46
2880	33.06	33.05	FALSE	12	60	2.68	0.46
3600	34.71	34.37	FALSE	12	60	2.68	0.46
4320	34.43	35.30	TRUE	13	60	2.68	0.46
5040	35.32	36.21	TRUE	13	70	3.09	0.53
5760	39.48	36.62	FALSE	13	70	3.09	0.53
6480	40.12	36.24	FALSE	13	70	3.09	0.53
7200	42.22	35.54	FALSE	13	70	3.09	0.53
7920	43.43	35.40	FALSE	13	70	3.09	0.53
8640	41.07	36.78	FALSE	13	70	3.09	0.53

Adjust Refill While in the CBC-fixed scenario the contract parameters are not changed, drivers can change their refill strategy. Table A.24 shows the change in refill condition of two driver agents, following eq. 6.10. This happens when the agent's profit during the monthly evaluation is lower than the average drivers' profit.

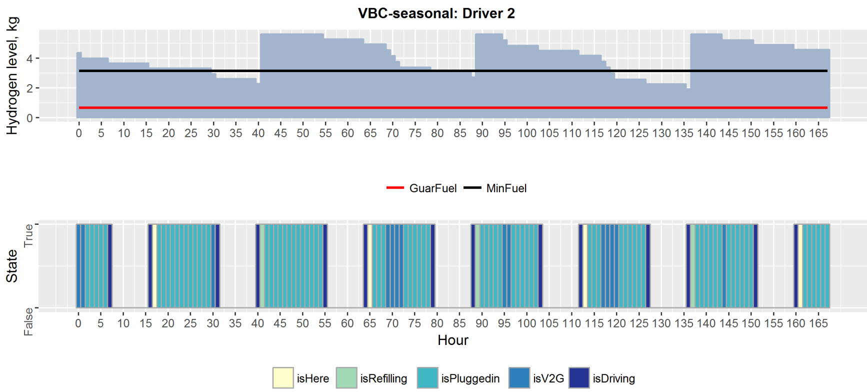
A.3.4. Extreme value testing

To perform tests for breaking the agents, extreme values were used. The main aspects to test are the driving schedules and the initialization of contracts. To do this, we tested 1) using equal arrival and departure times, 2) shortest parking durations and 2) initialization of volume-based contracts with a duration of 0.

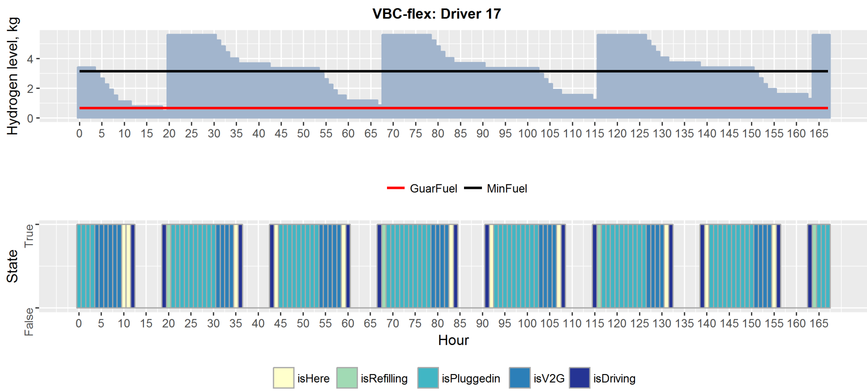
Single-agent testing

Equal arrival and departure times In volume-based scenarios, the driving occurs at the same time every day. The plug-in hours are also fixed. The refilling occurs before plugging in, when necessary. Figure A.7 shows the hydrogen level and the states of two driver agents with similar driving needs throughout the first week.

In control-based scenarios, the driving occurs around the same time every day, with a +-1 hour variation. The plug-in hours are defined by the fuel available and the hours of parking. The refilling occurs before plugging in, when necessary. Figure A.8 shows the



(a) VBC-seasonal

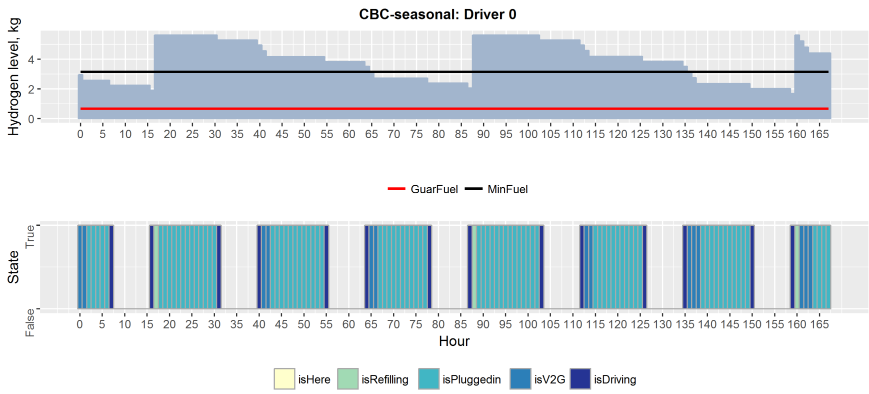


(b) VBC-flexible

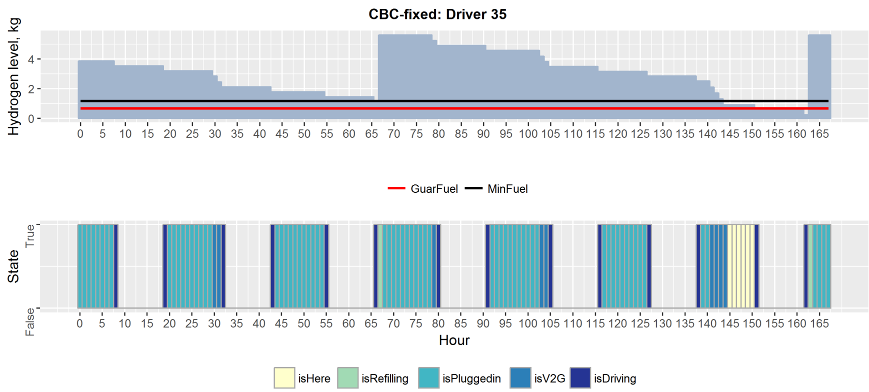
Figure A.5: Hydrogen level and states of two FCEVs throughout the first week

Table A.24: CBC-fixed: Adjusting refill conditionm driver with `DriverID` = 9

`Hour` time	`evalProfit` €	`AvgEvalProfitDrivers` €	`isAdjustRefill`	`refillCondition`
0	0.00	0.00	FALSE	0.1
720	37.42	42.77	TRUE	0.22
1440	38.89	43.18	TRUE	0.32
2160	41.83	43.18	TRUE	0.41
2880	43.96	44.08	TRUE	0.48
3600	44.52	44.10	FALSE	0.48
4320	43.83	44.30	TRUE	0.54
5040	44.19	44.32	TRUE	0.59
5760	43.85	44.34	TRUE	0.64
6480	45.31	44.21	FALSE	0.64
7200	45.26	44.20	FALSE	0.64
7920	46.30	43.58	FALSE	0.64
8640	45.63	43.72	FALSE	0.64

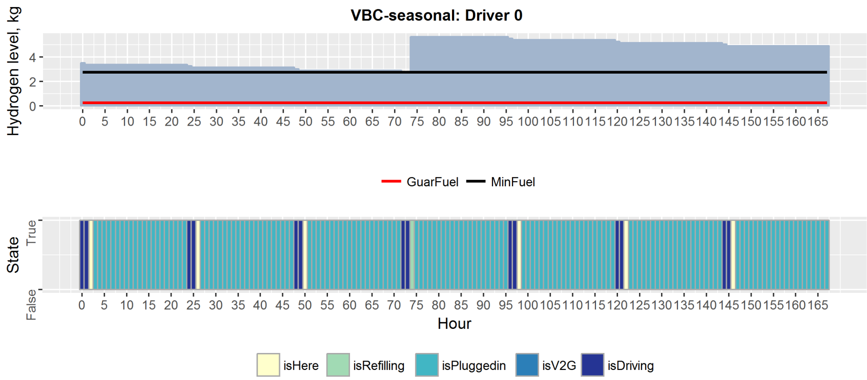


(a) CBC-seasonal

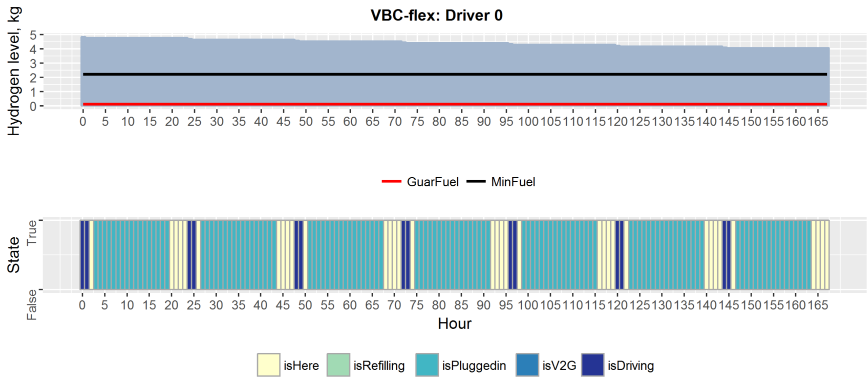


(b) CBC-fixed

Figure A.6: Hydrogen level and states of two FCEVs throughout the first week

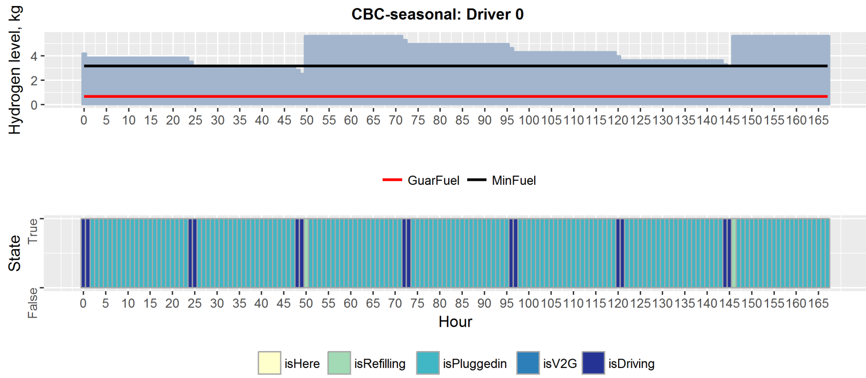


(a) VBC-seasonal

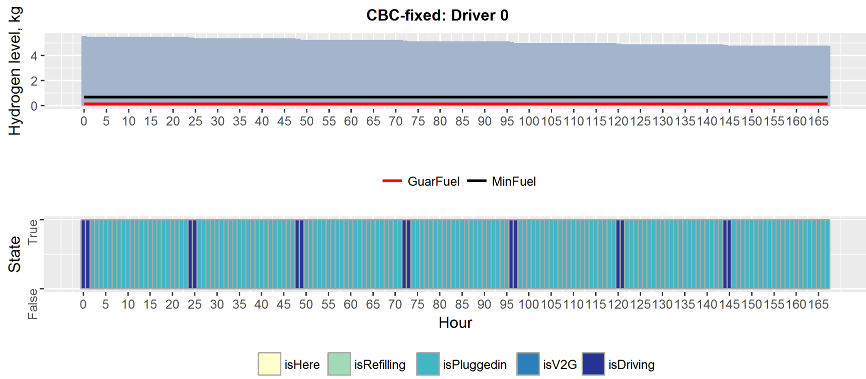


(b) VBC-flexible

Figure A.7: Hydrogen level and states of two FCEVs throughout the first week



(a) CBC-seasonal



(b) CBC-fixed

Figure A.8: Hydrogen level and states of two FCEVs throughout the first week

hydrogen level and the states of two driver agents with similar driving needs throughout the first week.

VBC-flexible: duration of 0 hours In the model, the shortest parking duration is 3 hours. This allows for the possibility of a minimum of one hour for vehicle-to-grid. When the arrival time is 23 hours and the departure time is 0 hours, the parking duration is 1 hour. To correct this, the model increases the parking duration by reducing the arrival time or increasing the departure time.

The VBC-flexible contracts allow the choice of different duration fractions, based on the parking duration. With a very low parking duration it is possible to see a contracted duration of 0 hours. This is confirmed in the set-up results of the VBC-flexible scenario.

Interaction testing in minimal model

VBC-flexible: duration of 0 hours By initializing contracts with a duration of 0 hours we tested the effects of zero participation in V2G on the system. As expected, with a

Table A.25: Drivers setup: VBC-flexible

Driver characteristics						V2G contract			
DriverID	arrival	departure	availableHours	parkingDuration	distance	duration	maxVol	minFuel	minfuelAvailability
	Time		Hours	Hours	km	Hours	kWh	kg	kg
0	23	2	1	3	20	0	0	0.12	0

Table A.26: Drivers setup: VBC-flexible

Driver characteristics						V2G contract			
DriverID	arrival	departure	availableHours	parkingDuration	distance	duration	maxVol	minFuel	minfuelAvailability
	Time		Hours	Hours	km	Hours	kWh	kg	kg
0	21	0	1	3	35	0	0	0.21	0
0	23	2	1	3	110	0	0	0.662	0

contracted duration of 0 hours, there are no vehicles available for V2G.

A.4. Additional results

In this section we present additional tables with results from the sensitivity analyses.

Table A.27: S1 Results: Change % in mean values of each performance indicator with respect to base case simulation

Indicator	VBC-flexible (S1)	CBC-fixed (S1)
R1: Self-supply electricity	-2%	-
R2: Self-supply hydrogen	-	-
E1: Mean elec. Price	-1%	-
E2: Profit: Hydrogen	-1%	-
E3: Costs: Electricity	-2%	-1%
E4: Profit: V2G	-14%	-2%
E5: Start-ups	12%	-3%
A1: Plug-in hours	-16%	-2%
A2: Refill count	-12%	-14%

Table A.28: S2 Results: Change percentage of average economic indicators with respect to base case simulation

Indicator	VBC-seasonal (S2)	VBC-flexible (S2)	CBC-seasonal (S2)	CBC-fixed (S2)
E1: Mean elec. Price	-8%	-7%	-11%	-11%
E2: Profit: Hydrogen	-1%	0%	-1%	-1%
E3: Costs: Electricity	-20%	-18%	-26%	-25%
E4: Profit: V2G	-79%	-78%	-84%	-83%
E5: Start-ups	1%	2%	0%	-2%

Table A.29: S3 Results: Change percentage of average economic indicators with respect to base case simulation

Indicator	VBC-seasonal (S3)	VBC-flexible (S3)	CBC-seasonal (S3)	CBC-fixed (S3)
S3.31 Hydrogen price 2.50 €/kg (+9%)				
E1: Mean elec. Price	6%	6%	6%	6%
E2: Profit: Hydrogen	197%	200%	196%	196%
E3: Costs: Electricity	5%	5%	5%	5%
E4: Profit: V2G	0%	2%	1%	3%
E5: Start-ups	0%	-1%	0%	-1%
S3.2 Hydrogen price 2.75 €/kg (+20%)				
E1: Mean elec. Price	13%	13%	13%	13%
E2: Profit: Hydrogen	433%	438%	429%	431%
E3: Costs: Electricity	11%	11%	10%	10%
E4: Profit: V2G	1%	3%	2%	2%
E5: Start-ups	0%	-1%	-1%	0%
S3.3 Hydrogen price 3.00 €/kg (+31%)				
E1: Mean elec. Price	21%	20%	20%	20%
E2: Profit: Hydrogen	666%	675%	664%	667%
E3: Costs: Electricity	17%	17%	16%	16%
E4: Profit: V2G	4%	3%	2%	3%
E5: Start-ups	0%	0%	-1%	0%

Table A.30: S4 Results: Change percentage of mean and standard deviation of economic indicators with respect to base case simulation

Indicator	VBC-seasonal (S4)	VBC-flexible (S4)	CBC-seasonal (S4)	CBC-fixed (S4)
E1: Mean elec. Price	-0.65%	-2.15%	-0.26%	-0.22%
E2: Profit: Hydrogen	0.79%	0.60%	-1.21%	-0.48%
E3: Costs: Electricity	-0.68%	-2.19%	-0.26%	-0.04%
E4: Profit: V2G	-0.05%	-0.39%	0.05%	1.35%
E5: Start-ups	0.04%	-0.25%	-0.52%	-0.77%

B

Car-Park Power Plant model

This appendix contains more details describing the agent-based model presented in Chapter 7, the Car-Park Power Plant. First, the complete list of driver and microgrid operator variables are presented, followed by the equations used to calculate the total costs of hydrogen. Then, the model verification shows the different tests performed to verify the agent-based model.

B.1. Full list of driver and aggregator variables

B.2. Total costs of hydrogen

To calculate the system levelized cost of hydrogen, we calculate the total costs of the system taking into account the following components: 1) Electrolyzer, 2) PV system, and 3) Hydrogen storage and refilling system (Hydrogen storage, compressor, dispenser, reverse osmosis, rainwater collector).
Total costs of electrolyzer (el):

$$TC_{el} = CC_{el} + OMC_{el} \tag{B.1}$$

$$CC_{el} = CC_{el}^{unit} \cdot P_{el}^{max} \cdot \frac{WACC \cdot (1+WACC)^{LT_{el}}}{((1+WACC)^{LT_{el}} - 1)} \tag{B.2}$$

$$OMC_{el} = CC_{el}^{unit} \cdot P_{el}^{max} \cdot OMC_{el}^{\%} \tag{B.3}$$

Total costs of PV system (PV):

$$TC_{PV} = CC_{PV} + OMC_{PV} \tag{B.4}$$

$$CC_{PV} = CC_{PV}^{unit} \cdot P_{PV} \cdot \frac{WACC \cdot (1+WACC)^{LT_{PV}}}{((1+WACC)^{LT_{PV}} - 1)} \tag{B.5}$$

$$OMC_{PV} = CC_{PV}^{unit} \cdot P_{PV} \cdot OMC_{PV}^{\%} \tag{B.6}$$

Table B.1: Driver variables

Variable	Description	Data type
	Driver properties	
`arrival`	Arrival time at car park	Integer
`departure`	Departure time from car park	Integer
`distance`	Daily distance traveled	Integer
`drivingSchedule`	Standard arrival and departure tiems	Integer (list)
`pProfile`	Parking profile	String
`refillCondition`	Decimal fraction used to decide whether or not to refill	Float
`isAdjustBehavior`	State indicating whether the driver is changing its behavior	Float
`minFuelDriving`	Daily fuel need for driving	Float
`fuelSF`	Safety factor to determine daily fuel need for driving	Float
`contract`	Vehicle-to-grid contract that specifies conditions for participation	Object
	Vehicle properties and states	
`fuelAvailability`	Decimal fraction indicating the fuel available for V2G	Float
`fuelMax`	Maximum hydrogen capacity in vehicle's tank	Float
`hydrogenLevel`	Current level of hydrogen	Float
`isDriving`	State indicating whether the driver is using the vehicle to drive	Boolean
`isRefilling`	State indicating whether the driver is using the vehicle to refill	Boolean
`isHere`	State indicating whether the driver is in the parking garage	Boolean
`isPluggedin`	State indicating whether the vehicle is plugged in	Boolean
`isV2G`	State indicating whether the vehicle is being used for V2G	Boolean
`isV2G_t`	List of V2G states, where True = 1 and False = 0	Integer (list)
`Hrefill`	Amount of hydrogen refilled in current time step	Float
`pFCEV`	Amount of power being delivered using the vehicle in current time step	Float
`startUps`	Total number of startUps	Float
	Techno-economic variables of vehicle use	
`energyCost`	Cost of producing 1 kWh of electricity using hydrogen	Float
`fuelCost`	Cost of hydrogen	Float
`costV2G`	Cost of supplying electricity using vehicle in current time step	Float
`profitV2G`	Profit from V2G supply	Float
`revenuesV2G`	Revenues for V2G supply	Float
`totalCapFactor`	Capacity factor of vehicle at the end of simulation	Float
`totalNetProfitV2G`	Total net profit at the end of simulation	Float
`totalPluginHours`	Total plug-in hours at the end of simulation	Float
`totalPotProfitV2G`	Total potential profit at the end of simulation	Float
`totalProfitV2G`	Total profit at the end of simulation	Float
`totalRevenuesV2G`	Total revenues at the end of simulation	Float
`totalVolume`	Total volume of electricity supplied at the end of simulation	Float
	Vehicle-to-grid evaluation	
`avgCapFactor`	Average capacity factor of drivers with same parking profile, during the evaluation period	Float
`avgRevenuesV2G`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`avgVolume`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`evalCapFactor`	Capacity factor of vehicle in evaluation period	Integer
`evalPluginHours`	Cumulative plug-in hours of current evaluation period	Integer
`evalPotProfitV2G`	Potential profit of current evaluation period	Integer
`evalProfitV2G`	Profit of current evaluation period	Integer
`evalRevenuesV2G`	Revenues of current evaluation period	Integer
`evalTimer`	Timer to indicate the hours of current evaluation period	Integer
`evalVolume`	Cumulative volume of V2G supplied during evaluation period	Float

Table B.2: Aggregator variables

Variable	Description	Data type
	Contracted drivers	
`drivers_list`	List of contracted drivers	Object (list)
`driversH_list`	List of contracted drivers with Home profile	Object (list)
`driversW_list`	List of contracted drivers with Work profile	Object (list)
`numDriversH`	Number of contracted drivers with Home profile	Integer
`numDriversW`	Number of contracted drivers with Work profile	Integer
	DAM participation and V2G	
`buyPrice_t`	List of buy price for day D+1	Float (list)
`buyVol_t`	List of buy volume for day D+1	Float (list)
`costsDA_t`	List of buy volume for day D+1	Float (list)
`costsV2G`	Cost of V2G (remuneration to drivers)	Float
`costsV2G_t`	List of V2G costs	Float (list)
`dispatchableFCEVs`	Number of vehicles that can be used for V2G	Integer
`dispatchedFCEVs`	Number of vehicles used for V2G	Integer
`drivers_available_list`	List of drivers that are available	Object (list)
`drivers_dispatchable_list`	List of drivers that are ready to be dispatched	Object (list)
`isDispatch`	State of CPPP as VPP	Object (list)
`isDispatch_t`	List of isDispatch throughout simulation	Object (list)
`market`	Day-ahead market	Object
`maxBuyPrice`	Maximum buy price in day-ahead market	Float
`minSellPrice`	Minimum sell price in day-ahead market	Float
`opBuyVol`	Actual electricity used from buy orders	Float
`opSellVol`	Actual electricity dispatched from sell orders	Float
`profitV2G`	Profit made with V2G	Float
profitV2G_t	List of profit made with V2G	Float (list)
`revenuesDA`	Hourly revenues from day-ahead market	Float
revenuesDA_t	List of revenues made with V2G	Float (list)
`schedFCEVs`	Number of FCEVs to be dispatched every hour	Float
`schedFCEVs_t`	Number of FCEVs to be dispatched every hour throughout the current day D	Float (list)
`schedVol_t`	Volume to be dispatched every hour throughout the current day D	Float (list)
`sellPrice_t`	List of sell price for day D+1	Float (list)
`sellVol_t`	List of buy volume for day D+1	Float (list)
`shortageFCEVs_t`	Shortage in number of vehicles every hour throughout the current day D	Float (list)
`totalCostsDA`	Total costs from day-ahead market	Float (list)
`totalCostsV2G`	Total costs of V2G (remuneration to drivers)	Float (list)
`totalProfitV2G`	Total profit of V2G operation	Float (list)
`totalRevenuesDA`	Total profit from day-ahead market	Float (list)
`totalV2G`	Total V2G supplied in day-ahead market during simulation period	Float
`unavailableFCEVs`	Number of vehicles present but not available for V2G	Float
	PV-Electrolyzer-Storage system	
`hSystem`	Hydrogen conversion and storage system	Object
`PVsystem`	PV system	Object
`profitHS_t`	List of profit made with hydrogen system	Float (list)
`revenuesHS_t`	List of revenues realized with hydrogen system	Float (list)
`totalProfitHS`	Total profit from hydrogen system at the end of the simulation	Float
`totalRevenuesHS`	Total revenues from hydrogen system at the end of the simulation	Float
	DAM evaluation	
`evalParticipants`	Number of participants with revenues	Object (list)
`avgCapFactorH`	Average capacity factor of drivers with same parking profile, during the evaluation period	Float
`avgRevenuesV2GH`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`avgVolumeH`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`avgCapFactorW`	Average capacity factor of drivers with same parking profile, during the evaluation period	Float
`avgRevenuesV2GW`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`avgVolumeW`	Average revenues of all drivers with same parking profile, during the evaluation period	Float
`evalTimer`	Timer to indicate the hours of current evaluation period	Integer

Total costs of hydrogen storage (HS):

$$TC_{HS} = CC_{HS} + OMC_{HS} \tag{B.7}$$

$$CC_{HS} = CC_{HS}^{unit} \cdot H_{HS}^{max} \cdot \frac{WACC \cdot (1+WACC)^{LT_{HS}}}{((1+WACC)^{LT_{HS}} - 1)} \tag{B.8}$$

$$OMC_{HS} = CC_{HS}^{unit} \cdot H_{HS}^{max} \cdot OMC_{HS}^{\%} \tag{B.9}$$

Total costs of compressor (c):

$$TC_c = CC_c + OMC_c \tag{B.10}$$

$$CC_c = \frac{CC_c^{unit}}{HHV} \cdot P_{el}^{max} \cdot \eta_{el} \cdot \frac{WACC \cdot (1+WACC)^{LT_c}}{((1+WACC)^{LT_c} - 1)} \tag{B.11}$$

$$OMC_c = \frac{CC_c^{unit}}{HHV} \cdot P_{el}^{max} \cdot \eta_{el} \cdot OMC_c^{\%} \tag{B.12}$$

Total costs of dispenser (d):

$$TC_d = CC_d + OMC_d \tag{B.13}$$

$$CC_d = CC_d^{unit} \cdot N_d^{max} \cdot \frac{WACC \cdot (1+WACC)^{LT_d}}{((1+WACC)^{LT_d} - 1)} \tag{B.14}$$

$$OMC_d = CC_d^{unit} \cdot N_d^{max} \cdot OMC_d^{\%} \tag{B.15}$$

Total costs of rain water collector (rw):

$$TC_{rw} = CC_{rw} + OMC_{rw} \tag{B.16}$$

$$CC_{rw} = CC_{rw}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot \frac{24}{1000} \cdot \frac{WACC \cdot (1+WACC)^{LT_{rw}}}{((1+WACC)^{LT_{rw}} - 1)} \tag{B.17}$$

$$OMC_{rw} = CC_{rw}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot \frac{24}{1000} \cdot OMC_{rw}^{\%} \tag{B.18}$$

Total costs of reverse osmosis (ro):

$$TC_{ro} = CC_{ro} + OMC_{ro} \tag{B.19}$$

$$CC_{ro} = CC_{ro}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot 24 \cdot \frac{WACC \cdot (1+WACC)^{LT_{ro}}}{((1+WACC)^{LT_{ro}} - 1)} \tag{B.20}$$

$$OMC_{rw} = CC_{ro}^{unit} \cdot \frac{P_{el}^{max} \cdot \eta_{el}}{HHV \cdot input_{w/kg}} \cdot 24 \cdot OMC_{rw}^{\%} \tag{B.21}$$

B.3. Model verification

B.3.1. Single-agent testing

To test a single driver agent we followed its states and verify whether they change as expected. There are 3 agent types in the model: the driver, the aggregator and the day-ahead market. The single-agent testing of the driver agent is possible by creating only one agent of each type. To test a single driver agent, we created one agent of each type in the 80SWHC-SU scenario. The methods `makeContract`, `drive`, `refill` and `plugin` were tested.

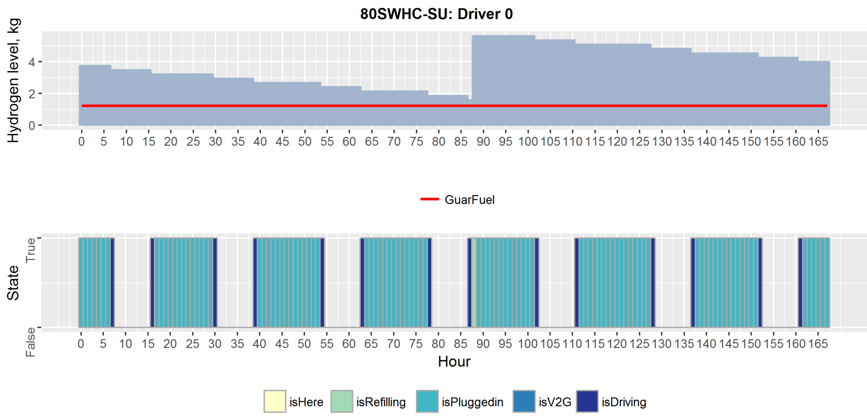


Figure B.1: Single agent testing: States of a driver agent throughout the first week

Make Contract

As Table B.3 shows, the parking hours are calculated as all the hours in which `isHere = True`. In this case, it is 15 hours. The actual available hours for V2G are 14 hours - 13 hours if there is refilling. The minimum fuel needed for driving is 0.81 kg, and the guaranteed fuel is calculated as 1.22 kg. This is due to the fuel safety factor of 1.5 defined in the simulation. The minimum price for V2G is defined as the cost of V2G, in €/MWh.

Drive, Refill, Plug-in

The drivers' daily actions can be observed following the change in state (drive, refill, plug-in, V2G) and the level of hydrogen in the tank.

Driving occurs twice every day at the same time, with a daily variability of -1 to +1. The plug-in hours are based on the hours that the vehicle is in the parking garage. The refilling occurs before plugging in, when necessary. Figure B.1 shows the hydrogen level and the states of a driver agent throughout the first week of the simulation.

B.3.2. Interaction testing in minimal model

For the interaction testing in a minimal model, we create a model with two driver agents, an aggregator agent and the day-ahead market agent. The following inputs are used to test the interactions in the minimal model:

- The minimum bid volume in the market is 10kW.
- The aggregator uses 50% of the contracted vehicles to place offers, i.e. always offers the capacity of 1 vehicle: 10kW.
- The number of discharger poles is equal to 1. Thus, there are four plug-in points available.

Aggregator

Plan and Operate According to the assumptions of the model, the aggregator has perfect foresight with respect to market prices. Assuming also that there will be enough

Table B.3: Single agent testing: Driver setup in 80SWHC-SU scenario

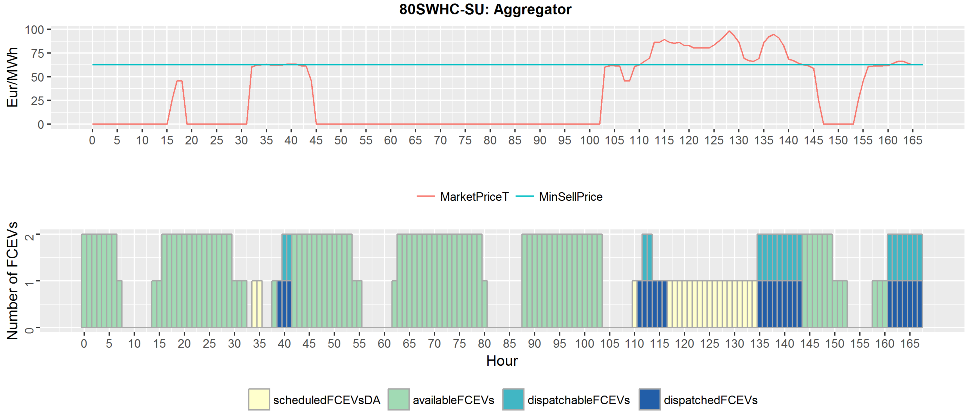
Driver characteristics							V2G contract			
ID	**Arrival**	**Departure**	**Distance**	**pProfile**	**pDuration**	**minFuelDriving**	**MinPrice**	**GuaranteedFuel**	**DriverMargin**	**EvalPeriod**
		Time	km		hours	kg	€/MWh	kg		hours
0	16	7	90	Home	15	0.81	62.50	1.22	0.63	720

vehicles, the aggregator makes a plan and offers V2G in the market whenever the market price exceeds the minimum sell price. FCEVs are scheduled for every hour of the next day (`scheduledFCEVsDA`). In this case, the capacity that the aggregator offers is always 50% of the contracted vehicles, thus 1 vehicle. Whenever market prices are high, the aggregator schedules vehicle in advance, as Fig.B.2 shows.

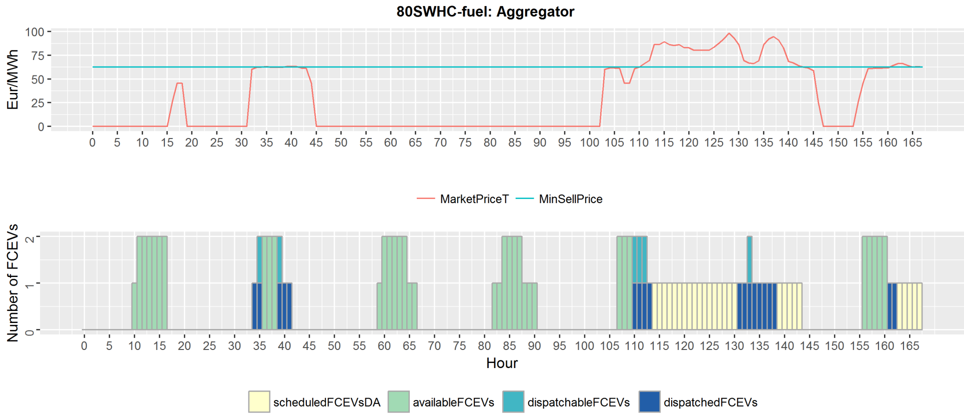
On the day itself,the aggregator looks for a vehicle to operate. This vehicle needs to have a `minPrice` lower than the market price. The minimum sell price of the aggregator is the average of all vehicles' `minPrice`.

As Fig. B.2a shows, there are hours in which FCEVs are scheduled between hour 117 and hour 128 (`scheduledFCEVsDA`), with 0 vehicles dispatched. This is because during those hours there are no dispatchable vehicles.

Settle Table B.4 and B.5 show the revenues, costs and profits for drivers and the aggregator, respectively. In the 80SWHC-SU scenario, we observe the revenues for the drivers at hour number 114, which corresponds to the costs for the aggregator. The same is observed in the 80SWHC-fuel scenario.



(a) 80SWHC-SU scenario



(b) 80SWHC-fuel scenario

Figure B.2: Interaction testing: Schedule of FCEVs based on market prices in different scenarios

Table B.4: Interaction testing: Drivers revenues and profit in one time step, 80SWHC-SU and 80SWHC-fuel scenarios

Scenario	ID	Hour	FuelAvailability	DMargin	isHere	isDriving	isPluggedin	isAvailable	isDispatchable	isV2G	pFCEV kW	RevsV2G	CostsV2G €	ProfitV2G
80SWHC-SU	0	114	0.31	0.35	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	0	0	0	0
80SWHC-SU	1	114	0.30	0.33	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	10	**0.70**	0.625	0.08
80SWHC-fuel	0	135	1	0.75	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	10	**0.80**	0.625	0.18
80SWHC-fuel	1	135	0.29	0.31	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	0	0	0	0

Table B.5: Interaction testing: Aggregator revenues and profit in 80SWHC-SU and 80SWHC-fuel scenarios

Scenario	Hour	MarketPriceT	MinSellPrice	V2GVol	DischargersUsed	DischargersAvailable	RevenuesDA	CostsV2G €	ProfitV2G
80SWHC-SU	114	86.35	62.50	10	2	2	0.86	**0.70**	0.16
80SWHC-fuel	135	86.35	62.5	10	2	2	0.86	**0.80**	0.06

Driver

In Table B.9 we show the initial contract parameters of the two drivers in each scenario. Figure B.3 and B.4 show the driver agents' states throughout one week.

Evaluate and Adjust strategy After every evaluation period, drivers can adjust their behavior if they are earning less than average. There are two strategies: adjusting the refilling behavior or adjusting the guaranteed fuel level in the V2G contract. This was tested in the minimal model.

Table B.6 shows the changes that occur in the drivers as a result of their adaptive behavior, in the 80SWHC-SU scenario. After every 30-day period, drivers evaluate their profit (`EvalProfit`) against the average of the two drivers (`AvgEvalProfit`). None of the two agents perform steadily better than the other, and therefore, at the end of the simulation, the refill condition has increased from 0.10 to 0.81 and 0.51. The fuel safety factor, on the other hand, has decreased in both agents, from 1.50 tp 0.58 and 1.08 - reducing the guaranteed fuel level in both drivers.

Table B.7 shows the changes of the two drivers throughout the year in the 80SWHC-fuel scenario. Similarly, there is one driver that has higher profits, and therefore its behavior is unchanged. The other one tries to increase its revenues by changing the refill condition and the fuel safety factor.

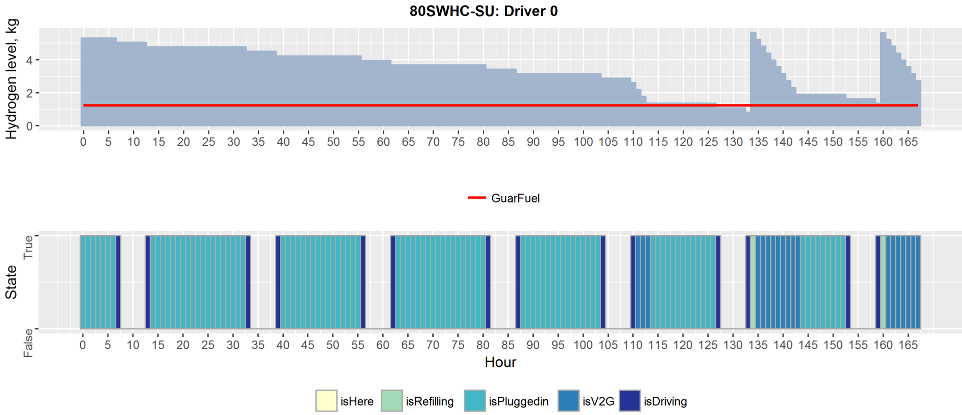
B.3.3. Multi-agent testing

Finally, we run the model 500 driver agents to verify once again the aggregator and driver methods.

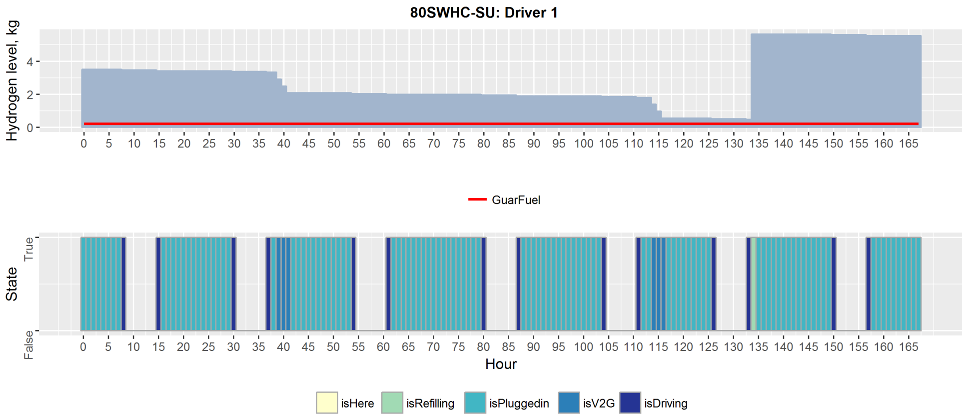
Aggregator

Fig B.5 shows the market prices and V2G operation in the multi-agent testing of the 80SWHC-SU scenario.

Settle Table B.8 and B.10 show the revenues, costs and profits for driver agents and the aggregator, respectively. In the 80SWHC-SU scenario, we observe the revenues for the drivers at hour number 115, which corresponds to the costs for the aggregator. The same is observed in the 80SWHC-fuel scenario.

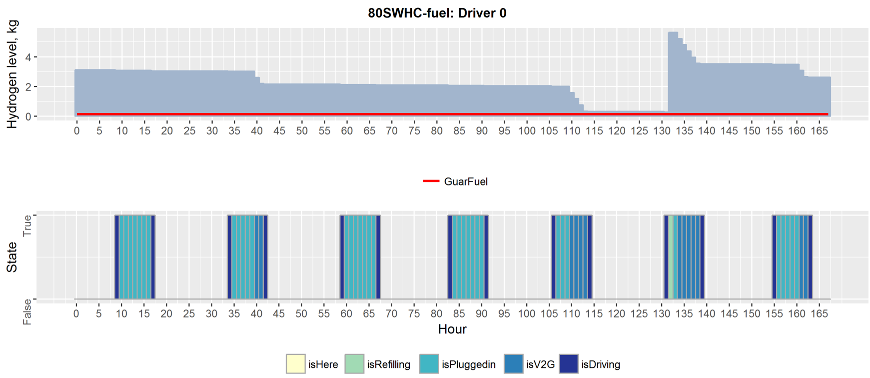


(a) Driver 0

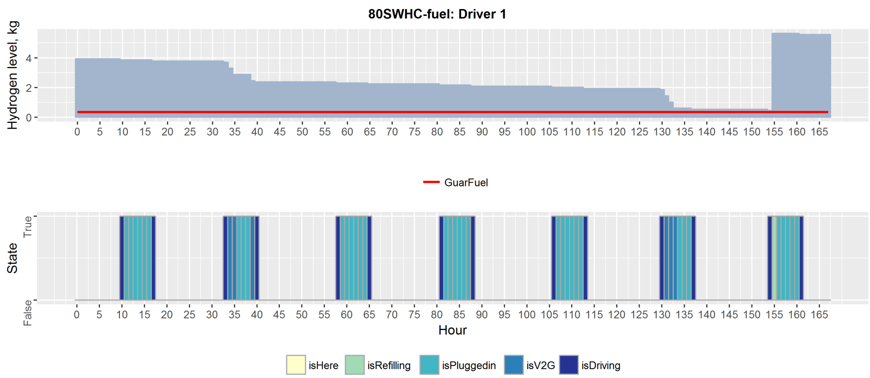


(b) Driver 1

Figure B.3: Interaction testing: States of two driver agents throughout the first week in the 80SWHC-SU scenario



(a) Driver 0



(b) Driver 1

Figure B.4: Interaction testing: States of two driver agents throughout the first week in the 80SWHC-fuel scenario

Table B.6: Interaction testing: Drivers evaluation and adjust strategy in 80SWHC-SU scenario

ID	Hour	EvalProfit	AvgEvalProfit	AdjRefill	RefillCondition	AdjContract	FuelSF	GuarFuel
0	0	-	-	FALSE	0.10	FALSE	1.50	1.22
0	720	32.47	27.47	FALSE	0.10	FALSE	1.50	1.22
0	1440	1.94	3.04	FALSE	0.10	TRUE	1.08	0.88
0	2160	3.24	2.88	FALSE	0.10	FALSE	1.08	0.88
0	2880	4.95	5.01	FALSE	0.10	TRUE	0.79	0.64
0	3600	3.62	4.51	TRUE	0.34	FALSE	0.79	0.64
0	4320	1.70	5.57	TRUE	0.51	FALSE	0.79	0.64
0	5040	8.79	9.40	FALSE	0.51	TRUE	0.58	0.47
0	5760	7.58	8.55	TRUE	0.63	FALSE	0.58	0.47
0	6480	18.54	14.49	FALSE	0.63	FALSE	0.58	0.47
0	7200	4.64	4.97	TRUE	0.71	FALSE	0.58	0.47
0	7920	13.38	15.91	TRUE	0.77	FALSE	0.58	0.47
0	8640	11.18	21.80	TRUE	0.81	FALSE	0.58	0.47
1	0	-	-	FALSE	0.10	FALSE	1.50	0.20
1	720	22.48	27.47	FALSE	0.10	TRUE	1.08	0.15
1	1440	4.14	3.04	FALSE	0.10	FALSE	1.08	0.15
1	2160	2.52	2.88	TRUE	0.34	FALSE	1.08	0.15
1	2880	5.06	5.01	FALSE	0.34	FALSE	1.08	0.15
1	3600	5.40	4.51	FALSE	0.34	FALSE	1.08	0.15
1	4320	9.45	5.57	FALSE	0.34	FALSE	1.08	0.15
1	5040	10.02	9.40	FALSE	0.34	FALSE	1.08	0.15
1	5760	9.52	8.55	FALSE	0.34	FALSE	1.08	0.15
1	6480	10.44	14.49	TRUE	0.51	FALSE	1.08	0.15
1	7200	5.31	4.97	FALSE	0.51	FALSE	1.08	0.15
1	7920	18.43	15.91	FALSE	0.51	FALSE	1.08	0.15
1	8640	32.42	21.80	FALSE	0.51	FALSE	1.08	0.15

Table B.7: Interaction testing:: Drivers evaluation and adjust strategy in 80SWHC-fuel scenario

ID	Hour	EvalProfit	AvgEvalProfit	AdjRefill	RefillCondition	AdjContract	FuelSF	GuarFuel
0	0	-	-	FALSE	0.1	FALSE	1.50	0.14
0	720	14.61	15.11	FALSE	0.1	TRUE	1.08	0.10
0	1440	1.79	2.22	TRUE	0.34	FALSE	1.08	0.10
0	2160	1.47	1.05	FALSE	0.34	FALSE	1.08	0.10
0	2880	1.15	0.58	FALSE	0.34	FALSE	1.08	0.10
0	3600	0.61	0.31	FALSE	0.34	FALSE	1.08	0.10
0	4320	0.23	0.12	FALSE	0.34	FALSE	1.08	0.10
0	5040	0.55	0.29	FALSE	0.34	FALSE	1.08	0.10
0	5760	1.64	1.25	FALSE	0.34	FALSE	1.08	0.10
0	6480	3.96	2.15	FALSE	0.34	FALSE	1.08	0.10
0	7200	1.04	0.86	FALSE	0.34	FALSE	1.08	0.10
0	7920	7.87	8.41	FALSE	0.34	TRUE	0.79	0.07
0	8640	13.89	13.78	FALSE	0.34	FALSE	0.79	0.07
1	0	-	-	FALSE	0.1	FALSE	1.50	0.34
1	720	15.62	15.11	FALSE	0.1	FALSE	1.50	0.34
1	1440	2.65	2.22	FALSE	0.1	FALSE	1.50	0.34
1	2160	0.63	1.05	FALSE	0.1	TRUE	1.08	0.24
1	2880	-	0.58	TRUE	0.34	FALSE	1.08	0.24
1	3600	-	0.31	TRUE	0.51	FALSE	1.08	0.24
1	4320	-	0.12	TRUE	0.63	FALSE	1.08	0.24
1	5040	0.02	0.29	FALSE	0.63	TRUE	0.79	0.18
1	5760	0.86	1.25	FALSE	0.63	TRUE	0.58	0.13
1	6480	0.35	2.15	TRUE	0.71	FALSE	0.58	0.13
1	7200	0.68	0.86	TRUE	0.77	FALSE	0.58	0.13
1	7920	8.95	8.41	FALSE	0.77	FALSE	0.58	0.13
1	8640	13.67	13.78	FALSE	0.77	TRUE	0.44	0.10

Table B.8: Multi-agent testing: Drivers revenues and profit at hour 126 in 80SWHC-SU scenario

ID	**FuelAvailability**	**DMargin** kW	**RevsV2G**	**CostsV2G** €	**ProfitV2G**
57	0.55	0.61	0.78	0.625	0.15
60	0.91	0.75	0.82	0.625	0.19
70	0.44	0.51	0.75	0.625	0.13
75	0.83	0.75	0.82	0.625	0.19
76	0.93	0.75	0.82	0.625	0.19
111	1.00	0.75	0.82	0.625	0.19
117	1.00	0.75	0.82	0.625	0.19
128	0.79	0.75	0.82	0.625	0.19
162	0.51	0.58	0.77	0.625	0.15
174	0.68	0.71	0.81	0.625	0.18
185	0.32	0.36	0.72	0.625	0.09
187	0.23	0.25	0.69	0.625	0.06
189	0.75	0.75	0.82	0.625	0.19
206	0.57	0.62	0.78	0.625	0.16
215	0.62	0.66	0.79	0.625	0.17
219	1.00	0.75	0.82	0.625	0.19
223	0.73	0.74	0.81	0.625	0.19
228	0.45	0.52	0.76	0.625	0.13
238	0.74	0.75	0.82	0.625	0.19
246	0.95	0.75	0.82	0.625	0.19
255	0.75	0.75	0.82	0.625	0.19
286	0.74	0.74	0.81	0.625	0.19
290	0.87	0.75	0.82	0.625	0.19
314	0.77	0.75	0.82	0.625	0.19
324	0.55	0.61	0.78	0.625	0.15
329	0.47	0.54	0.76	0.625	0.14
346	0.92	0.75	0.82	0.625	0.19
347	0.88	0.75	0.82	0.625	0.19
349	1.00	0.75	0.82	0.625	0.19
379	0.68	0.71	0.81	0.625	0.18
408	0.76	0.75	0.82	0.625	0.19
414	0.62	0.67	0.80	0.625	0.17
422	0.85	0.75	0.82	0.625	0.19
425	0.87	0.75	0.82	0.625	0.19
452	0.69	0.71	0.81	0.625	0.18
458	0.76	0.75	0.82	0.625	0.19
467	0.12	0.25	0.69	0.625	0.06
470	1.00	0.75	0.82	0.625	0.19
474	0.22	0.25	0.69	0.625	0.06
491	0.74	0.74	0.81	0.625	0.19
Total			**31.73**	25.00	6.73

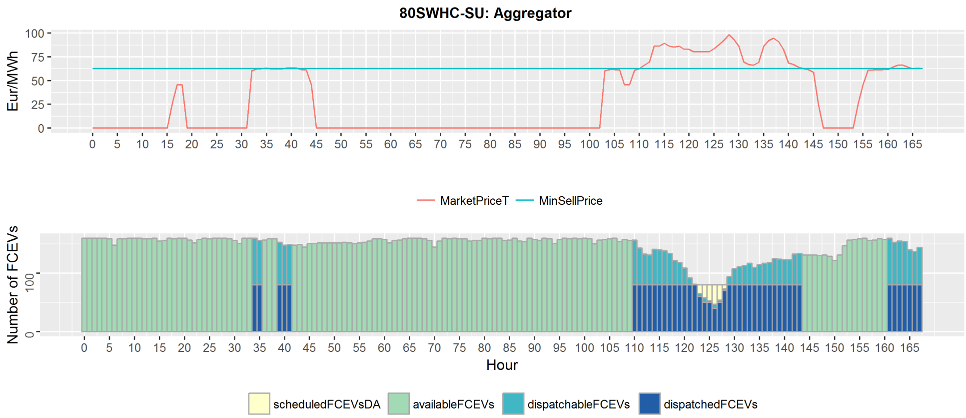


Figure B.5: Multi-agent testing: Schedule of FCEVs based on market prices in the 80SWHC-SU scenario

Table B.9: Interaction testing: Drivers setup in 80SWHC-SU and 80SWHC-fuel scenarios

	Driver characteristics							V2G contract			
Scenario	**ID**	**Arrival**	**Departure**	**Distance**	**pProfile**	**pDuration**	**minFuelDriving**	**MinPrice**	**GuaranteedFuel**	**DriverMargin**	**EvalPeriod**
		Time		km		hours	kg	€/MWh	kg		hours
80SWHC-SU	0	14	8	90	Home	18	0.81	62.50	1.22	0.75	720
80SWHC-SU	1	14	7	15	Home	17	0.14	62.50	0.20	0.66	720
HWMC-fuel	0	10	18	10	Work	8	0.09	62.50	0.14	0.60	720
HWMC-fuel	1	9	16	25	Work	7	0.23	62.50	0.34	0.70	720

Table B.10: Multi-agent testing: Aggregator revenues and profit at hour 126 in 80SWHC-SU scenario

Hour	**MarketPriceT**	**MinSellPrice**	**V2GVol**	**DischargersUsed**	**DischargersAvailable**	**RevenuesDA**	**CostsV2G**	**ProfitV2G**
							€	
126	87.88	62.50	400	155	5	35.15	**31.73**	3.42

Driver
Figure B.6a and B.6b show the driver agents' states throughout one week, in the multi-agent testing.

Evaluate and Adjust strategy Finally, the evaluation and adaptive behavior of driver agents is shown in Figure B.7. The initial values for the refill condition and fuel safety factor are 0.10 and 1.50 respectively. At the end of the year, there are some drivers that still have the initial properties, but many drivers have adjusted them after each evaluation period.

B.3.4. Extreme value testing

Single-agent testing
To test extreme values in a single agent model, we carry out the following tests:

1. Create a driver agent with "Home" parking profile, with equal arrival and departure times = 0h.

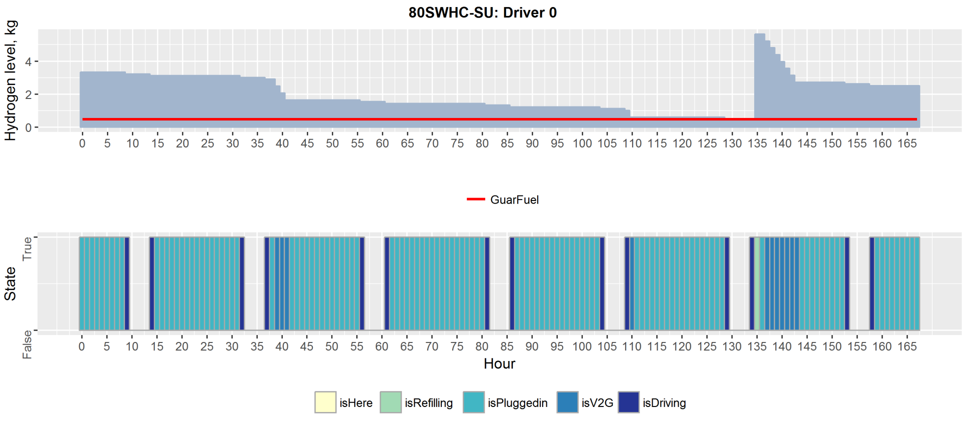
2. Create a driver agent with "Work" parking profile, with equal arrival and departure times = 23h.

Table B.11 shows the setup characteristics of a single agent in the two cases.

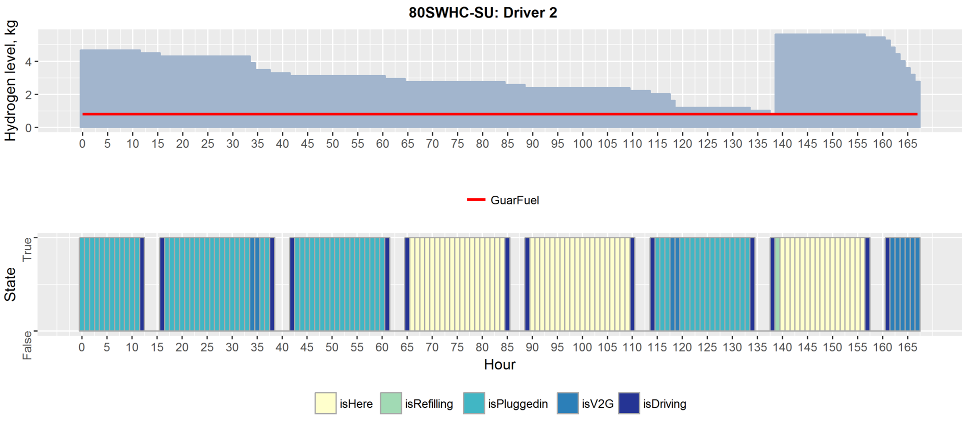
As expected, in the first case, the model corrects one of the two times to allow a maximum parking duration of 23 hours: this includes the arrival time, an hour for possible refilling, and an hour for possible V2G. Although at the arrival time vehicles are not available, it is still considered as 'parking time' because the `isHere` state of the vehicle is `True`. In the second case, the model corrects one the two times, from 23 to 20 hours, to allow a minimum parking duration of 3 hours.

As Fig. B.8 shows, the vehicle is plugged in right after arrival for two hours and then is driving away. Because of the driving schedule in Test 1 (1 h and 0 h) the daily driving variability is restricted to 0 hours. In Test 2, on the other hand, the daily driving variability is defined between 0 and +1.

Interaction testing in minimal model
In the interaction testing, we created two agents with different parking profiles and gave both of them an arrival and departure time of 0h. As shown in Table B.12, both adjust the times to keep the parking duration from within the lower and higher bounds of 3 and 23 hours. Figure B.9 shows the states of the two driver agents and the aggregator throughout the first week. The driver agent with a longer parking duration time is used more often to provide vehicle-to-grid.

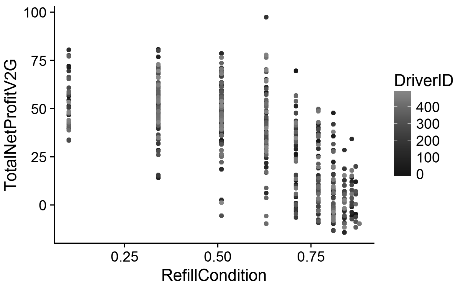


(a) Driver 0

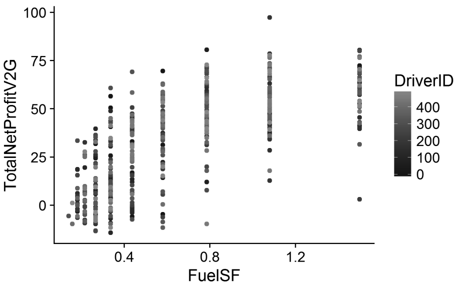


(b) Driver 2

Figure B.6: Multi-agent testing: States of two driver agents throughout the first week in the 80SWHC-SU scenario

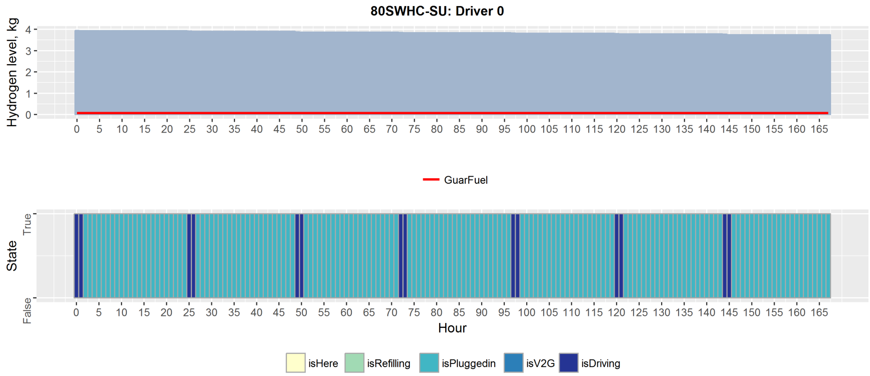


(a) Refill condition vs net profit

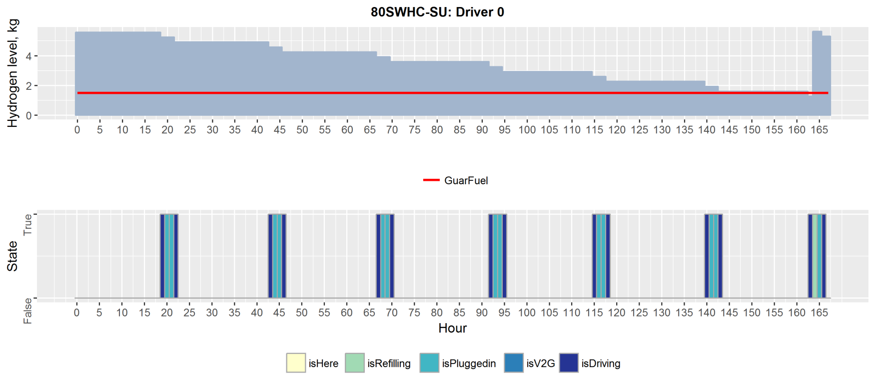


(b) Fuel safety factor vs net profit

Figure B.7: Multi-agent testing: evaluation and adjust strategy of drivers, 80SWHC-SU scenario



(a) Test 1: Home profile, equal arrival and departure times = 0 h



(b) Test2: Work profile, equal arrival and departure times = 23 h

Figure B.8: Extreme value, single-agent testing: States of a driver agent throughout the first week

Table B.11: Extreme value, single-agent testing: Driver setup in 80SWHC-SU scenario

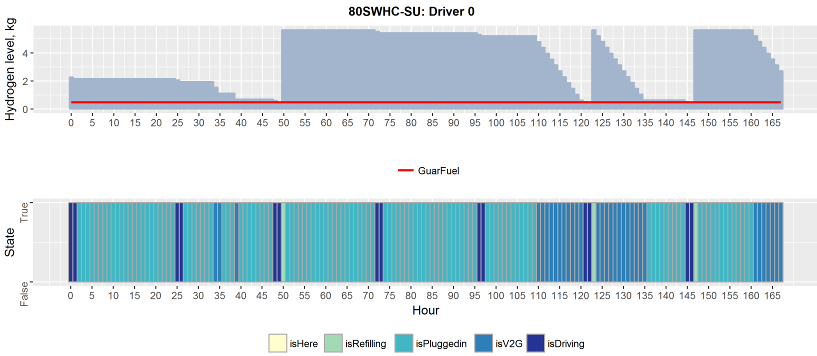
	Driver characteristics							V2G contract			
Test	**DriverID**	**Arrival**	**Departure**	**Distance**	**pProfile**	**pDuration**	**minFuelDriving**	**MinPrice**	**GuaranteedFuel**	**DriverMargin**	**EvalPeriod**
		Time		km		hours	kg	€/MWh	kg		hours
1	0	1	0	5	Home	23	0.05	62.50	0.07	0.72	720
2	0	20	23	110	Work	3	0.99	62.50	1.49	0.75	720

Table B.12: Extreme value, interaction testing: Driver setup in 80SWHC-SU scenario

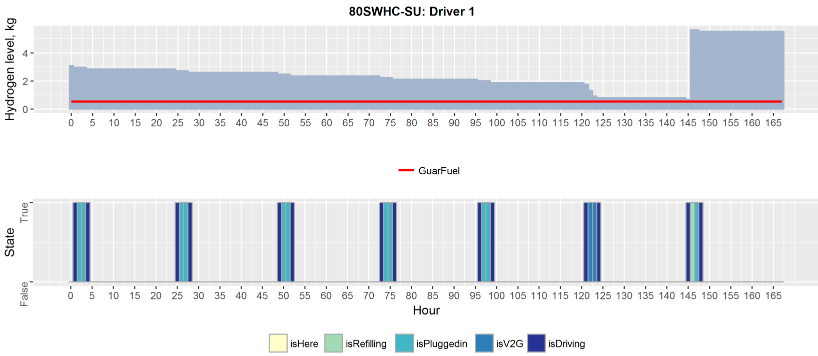
Driver characteristics							V2G contract			
DriverID	**Arrival**	**Departure**	**Distance**	**pProfile**	**pDuration**	**minFuelDriving**	**MinPrice**	**GuaranteedFuel**	**DriverMargin**	**EvalPeriod**
	Time		km		hours	kg	€/MWh	kg		hours
0	1	0	35	Home	23	0.32	62.50	0.47	0.43	720
0	1	0	3	Work	3	0.36	62.50	0.54	0.57	720

B.4. Additional results

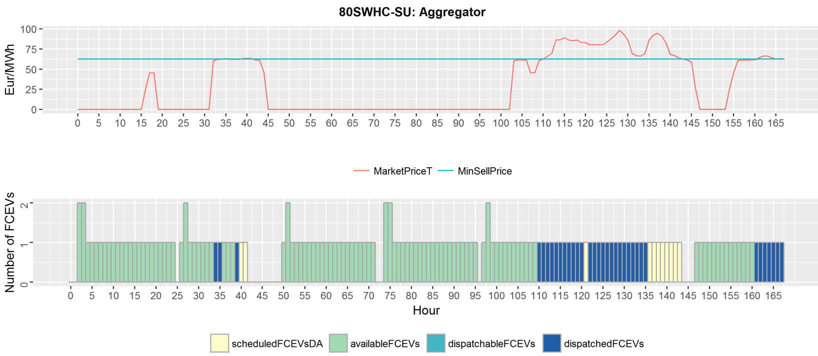
In this section we present additional tables with results from the sensitivity analyses.



(a) Driver 0: Home profile



(b) Driver 1: Work profile



(c) Aggregator: Market prices and V2G operation

Figure B.9: Extreme value, interaction testing: States of driver agents and aggregator throughout the first week

Nomenclature

Table B.13: Indices

Index	Description
h	Households, where $h = 1...H$
i	FCEV units or drivers, where $i = 1...N$
j	Microgrid Operator
k	Aggregator
t	Time steps, where $t = 1...T$

Table B.14: Binary variables

Variable	Description
SU_{it}	Start-up of FCEV i at time t
SD_{it}	Shut-down of FCEV i at time t
x_{it}	V2G status of FCEV i at time t
y_{it}	Refilling status of FCEV i at time t
z_{it}	Location status of FCEV i at time t

Table B.15: Technical parameters

Variable	Description	Units
E_{fcev}	Hydrogen consumption per km driven	kg/km
η_{el}	Conversion efficiency of electrolysis	%
η_{FC}	Conversion efficiency of fuel cell in FCEVs	%
HHV	Higher heating value of hydrogen	kWh/kg
LHV	Low heating value of hydrogen	kWh/kg

Table B.16: General variables

Variable	Description	Units
Δt	Time step duration	hours
D_i^{exp}	Expected driving distance for FCEV i at time t	km
D_{it}^{dr}	Distance driven by FCEV i at time t	km
FA_{it}	Fuel availability of driver i at time t	-
H_{i0}	Initial amount of hydrogen stored in FCEVs	kg
$H_{i,min}$	Minimum limit for hydrogen stored in FCEVs	kg
H_{it}	Amount of hydrogen in FCEV i at time t	kg
H_{it}^{exp}	Hydrogen needed for expected driving needs	kg
H_{it}^{ref}	Amount of hydrogen refilled by driver i at time t	kg
$H_{max}^{el1\|2}$	Max. production capacity, electrolyzers 1, 2	kg/h
H_{max}^{ref}	Maximum hydrogen refilling quantity	kg
H_{min}^{ref}	Minimum hydrogen refilling quantity	kg
H_t^{exp}	Amount of hydrogen exported at time t	kg
H_t^{imp}	Amount of hydrogen imported at time t	kg
H_t^{prod}	Amount of hydrogen produced at time t	kg
H_t^{ref}	Total amount of hydrogen refilled at time t	kg
HS_{max}	Maximum amount of hydrogen in storage system	kg
HS_{min}	Minimum amount of hydrogen in storage system	kg
HS_t	Hydrogen storage quantity at time t	kg
K_t	Imbalance in the microgrid	kW
N_{max}^{ref}	Maximum sum of FCEVs refilling at any time t	–
N_t^{fcev}	Number of FCEVs needed for V2G at time t	–
$P_t^{el1\|2}$	Power used in electrolyzers 1, 2 at time t	kW
$P_t^{ex1\|2}$	Power exchanged with the grid at time t	kW
P_{it}^{fcev}	Power output of FCEV i at time t	kW
P_{max}^{fcev}	Maximum generation capacity of FCEVs	kW
P_{pop}	Preferred operating point of FCEVs for V2G	kW
P_t^{el}	Power output of electrolyzer at time t	kW
P_t^{exp}	Power exported at time t	kW
P_t^{imp}	Power imported at time t	kW
P_t^{load}	Aggregated load at time t	kW
P_t^{PV}	Aggregated PV generation at time t	kW
P_t^{V2G}	Power output of all vehicles at time t	kW
P_t^{wind}	Aggregated wind generation at time t	kW
sf	Safety factor for minimum hydrogen in tank	–

Table B.17: Economic parameters

Variable	Description	Units
$c_h^{contract}$	Annual contract cost for household	€
c_h^e	Annual cost of electricity for household	€
$c_h^{e,gross}$	Annual gross cost of electricity for household	€
c_i	Total costs for driver i over a period	€
$c_i^{contract}$	Annual contracting cost for driver i	€
c_i^{ref}	Total refilling costs for driver i over a period	€
c_{it}^{ref}	Cost of refilling for driver i at time t	€
c_i^{V2G}	Total V2G costs for driver i over a period	€
c_{jt}^{imp}	Cost of electricity imports for microgrid operator at time t	€
c_{jt}^{V2G}	Microgrid Operator cost of remunerating V2G to drivers at time t	€
c_k	Total costs for aggregator over a period	€
c_{kt}^{DA}	Aggregator costs in DA market at time t	€
c_{kt}^{V2G}	Aggregator cost of remunerating V2G to drivers at time t	€
c_{V2G}	Unit cost of V2G using hydrogen as fuel	€/kWh
m_{V2G}	Profit margin of driver for V2G price calculation	-
m_{it}^{V2G}	Profit margin of driver i at time t as specified in V2G contract	-
$netprofit_i^{V2G}$	Annual net profit of driver i from V2G	€
$p_{t,H2}$	Unit price of hydrogen at time t	€/kWh
p_{H2}	Unit price of hydrogen	€/kg
p_{imp}	Price of imported electricity	€/kWh
p_i^{V2G}	Minimum V2G price for driver i	€/kWh
p_{PV}	Price of electricity from PV	€/kWh
p_{V2G}	Price of V2G electricity	€/kWh
p_{V2GC}	Price of V2G capacity	€/kW-h
$profit_i^{V2G}$	Annual profit of driver i from V2G	€
$profit_j^e$	Annual profit of Microgrid operator from electricity sales	€
$profit_j^{HS}$	Annual profit of Microgrid operator from Hydrogen Storage system	€
$profit_k^{HS}$	Annual profit of Aggregator from Hydrogen Storage system	€
$profit_k^{V2G}$	Annual profit of Aggregator from V2G supply	€
p_t^{cap}	Capacity price paid by households	€/kWh
p_t^{DA}	Price at time t in Day-Ahead market	€/kWh
p_t^{en}	Energy price in microgrid at time t	€/kWh
p_t^{el}	Total electricity price in microgrid at time t	€/kWh
p_{V2G}	Unit price of V2G	€/kWh
r_i	Total revenues for for driver i over a period	€
r_{it}^{V2GC}	Revenues from V2G capacity for driver i at time t	€
r_{it}^{V2G}	Revenues from V2G supply for driver i at time t	€
r_{it}^{V2GE}	Revenues from V2G energy for driver i at time t	€
r_j	Total revenues for microgrid operator over a period	€
r_{jt}^e	Revenues from electricity sale for microgrid operator at time t	€
$r_{jt}^{e,exp}$	Revenues from electricity exports for microgrid operator at time t	€
r_k	Total revenues for aggregator over a period	€
r_{kt}^{DA}	Revenues from the day-ahead market for aggregator at time t	€
r_{kt}^{HS}	Revenues from the Hydrogen Storage system for aggregator at time t	€

Table B.18: Total costs, variables and system components

Variable	**Description**	**Units**
c	System component: Compressor	–
CC	Capital costs of system component	€
d	System component: Dispenser	–
el	System component: Electrolyzer	–
FC	System component: Fuel cell	–
HS	System component: Hydrogen Storage system	–
$hydrogen$	Hydrogen production	
LT	Lifetime of component	hours
OMC	Operation and maintenance costs of component	€
PV	Solar photovoltaic system	–
ro	System component: Reverse osmosis	–
rw	System component: Rain water collector	–
TC	Total costs	€
$wind$	System component: Wind turbine	–
$WACC$	Weighted average cost of capital	%

Bibliography

Alavi, F., Park Lee, E., van de Wouw, N., De Schutter, B., & Lukszo, Z. (2017). Fuel cell cars in a microgrid for synergies between hydrogen and electricity networks. *Applied Energy*, *192*, 296–304. doi: 10.1016/j.apenergy.2016.10.084

Bots, P. W. (2007). Design in socio-technical system development: three angles in a common framework. *Journal of Design Research*, *5*(3), 382. doi: 10.1504/JDR.2007.014883

BP. (2017). *Statistical Review of World Energy.* Retrieved 2017-11-10, from `https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html`

Broneske, G., & Wozabal, D. (2017, feb). How Do Contract Parameters Influence the Economics of Vehicle-to-Grid? *Manufacturing & Service Operations Management*, *19*(1), 150–164. doi: 10.1287/msom.2016.0601

Carlsson, B., & Stankiewicz, R. (1991). On the nature, function and composition of technological systems. *Journal of Evolutionary Economics*, *1*(2), 93–118. doi: 10.1007/BF01224915

Centraal Bureau voor de Statistiek (CBS), & Rijkswaterstaat (RWS). (2015). *Onderzoek Verplaatsingen in Nederland 2014 (Research on Movements in the Netherlands 2014) - Data Archiving and Networked Services (in Dutch).* Retrieved 2015-12-03, from `http://dx.doi.org/10.17026/dans-x95-5p7y` doi: http://dx.doi.org/10.17026/dans-x95-5p7y

Chappin, E. J. L. (2011). *Simulating energy transitions.* Delft University of Technology.

Crawford, S. E. S., & Ostrom, E. (1995). A Grammar of Institutions. *American Political Science Review*, *89*(03), 582–600.

De Bruijn, H., & Herder, P. M. (2009). System and actor perspectives on sociotechnical systems. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, *39*(5), 981–992. doi: 10.1109/TSMCA.2009.2025452

Dijk, M., Orsato, R. J., & Kemp, R. (2013). The emergence of an electric mobility trajectory. *Energy Policy*, *52*(0), 135–145. doi: 10.1016/j.enpol.2012.04.024

Ecofys. (2014). *Flexibility options in electricity systems* (Tech. Rep.).

Energie Data Services Nederland (EDSN). (2013). *Verbruiksprofielen - Profielen Elektriciteit 2014 (Load profiles - Electricity profiles 2015) (in Dutch).* Retrieved 2016-01-25, from `http://nedu.nl/portfolio/verbruiksprofielen/`

Energie Koplopers. (2016). *Flexibility from residential power consumption: A new market filled with opportunities* (Tech. Rep.).

ENTSO-E. (2017). *ENTSO-E Transparency Platform.* Retrieved 2017-10-30, from `https://transparency.entsoe.eu/`

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, *4*(5), 41–60. doi: 10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F

European Commission. (2016). *Commission proposes new rules for consumer centered clean energy transition.* Retrieved 2017-01-23, from https://ec.europa.eu/energy/en/news/commission-proposes-new-rules-consumer-centred-clean-energy-transition

European Environment Agency. (2017). *Renewable Energy in Europe* (Tech. Rep. No. December). EEA. Retrieved from https://www.eea.europa.eu/publications/renewable-energy-in-europe doi: 10.1016/0960-1481(94)90358-1

European Union. (2012). *Roadmap 2050* (Tech. Rep.). Retrieved from http://www.roadmap2050.eu/

European Union. (2018). *Sector coupling: how can it be enhanced in the EU to foster grid stability and decarbonise ?* (Tech. Rep. No. November). Brussels: Policy Department for Economic, Scientific and Quality of Life Policies.

European Union, & IRENA. (2018). *Renewable Energy Prospects for the European Union* (Tech. Rep. No. February).

Farahani, S. S., van der Veen, R., Oldenbroek, V., Alavi, F., Par Lee, E. H., van de Wouw, N., … Lukszo, Z. (2019). A Hydrogen-Based Integrated Energy and Transport System: The Design and Analysis of the Car as Power Plant Concept. *IEEE Systems, Man, and Cybernetics Magazine*, *5*(1), 37–50. doi: 10.1109/MSMC.2018.2873408

Flath, C. M. (2013). *Flexible Demand in Smart Grids: Modeling and Coordination* (Unpublished doctoral dissertation).

Freeman, G. M., Drennen, T. E., & White, A. D. (2017, jul). Can parked cars and carbon taxes create a profit? The economics of vehicle-to-grid energy storage for peak reduction. *Energy Policy*, *106*(March), 183–190. doi: 10.1016/j.enpol.2017.03.052

Ghorbani, A. (2013). *Structuring Socio-technical Complexity: Modelling Agent Systems Using Institutional Analysis.* Next Generation Infrastructures Foundation.

Goodin, R. E. (1998). *The theory of institutional design.* Cambridge University Press.

Gough, R., Dickerson, C., Rowley, P., & Walsh, C. (2017). Vehicle-to-grid feasibility: A techno-economic analysis of EV-based energy storage. *Applied Energy*, *192*, 12–23. doi: 10.1016/j.apenergy.2017.01.102

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., … DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*(1-2), 115–126. doi: 10.1016/j.ecolmodel.2006.04.023

Gui, E. M., Diesendorf, M., & MacGill, I. (2016). Distributed energy infrastructure paradigm: Community microgrids in a new institutional economics context. *Renewable and Sustainable Energy Reviews*(August), 0–1. doi: 10.1016/j.rser.2016.10.047

Guille, C., & Gross, G. (2009). A conceptual framework for the vehicle-to-grid (V2G) implementation. *Energy Policy*, *37*(11), 4379–4390. doi: http://dx.doi.org/10.1016/j.enpol.2009.05.053

He, X., Keyaerts, N., Azevedo, I., Meeus, L., Hancher, L., & Glachant, J. M. (2013). How to engage consumers in demand response: A contract perspective. *Utilities Policy*, *27*, 108–122. doi: 10.1016/j.jup.2013.10.001

Henning, H.-M., & Palzer, A. (2015). *What will the energy transformation cost?: Pathways* *for transforming the German energy system by 2050* (Tech. Rep.). Fraunhofer ISE.

Hodgson, G. M. (2006). What are institutions? *Journal of Economic Issues*, *XL*(1), 1–25. doi: Article

Holland, J. H. (1992). Complex adaptive systems. *Daedalus*, *121*(1), 17–30. Retrieved from `http://www.jstor.org/stable/20025416`

Holttinen, H., Tuohy, A., Milligan, M., Silva, V., Müller, S., & Soder, L. (2013). The Flexibility Workout. *IEEE Power and Energy Magazine*, *11*(6), 53–62. doi: 10.1109/MPE.2013.2278000

Hughes, T. (1989). The Evolution of Large Technological Systems. In W. Bijker, T. Hughes, & T. Pinch (Eds.), *The social construction of technological systems* (pp. 51–82). Cambridge MA: MIT Press.

Hydrogen Tools. (n.d.). *Hydrogen production energy conversion efficiencies.* Retrieved 2015-08-20, from `https://h2tools.org/hyarc/hydrogen-production`

Ipakchi, A., & Albuyeh, F. (2009). Grid of the future. *IEEE Power and Energy Magazine.*

IRENA, IEA, & REN21. (2018). *Renewable Energy Policies in a Time of Transition* (Tech. Rep.). IRENA, OECD/ IEA and REN21.

Kempton, W., & Kubo, T. (2000). Electric-drive vehicles for peak power in Japan. *Energy Policy*, *28*(1), 9–18. doi: 10.1016/S0301-4215(99)00078-6

Kempton, W., & Letendre, S. E. (1997, oct). Electric vehicles as a new power source for electric utilities. *Transportation Research Part D: Transport and Environment*, *2*(3), 157–175.

Kempton, W., & Tomić, J. (2005a). Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *Journal of Power Sources*, *144*(1), 268–279. doi: 10.1016/j.jpowsour.2004.12.025

Kempton, W., & Tomić, J. (2005b). Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *Journal of Power Sources*, *144*(1), 280–294. doi: 10.1016/j.jpowsour.2004.12.022

Khan, A. S. M., Verzijlbergh, R. A., Sakinci, O. C., & De Vries, L. J. (2018). How do demand response and electrical energy storage affect (the need for) a capacity market? *Applied Energy*, *214*(July 2017), 39–62. doi: 10.1016/j.apenergy.2018.01.057

Kissock, J. (1998). Combined heat and power for buildings using fuel-cell cars. In *Asme international solar energy conference* (pp. 121–132).

Koirala, B. (2017). *Integrated Community Energy Systems* (Doctoral dissertation). doi: 10.4233/uuid:10d555dd-8f03-4986-b5bf-ef09a63c92e1

Koliou, E. (2016). *Demand Response policies for the implementation of Smart Grids* (Doctoral dissertation, Delft University of Technology). doi: 10.4233

Koppenjan, J., & Groenewegen, J. (2005). Institutional design for complex technological systems. *International Journal of Technology, Policy and Management*, *5*(3), 240–257. doi: http://dx.doi.org/10.1504/IJTPM.2005.008406

Kroesen, M., Molin, E. J., & van Wee, B. (2011). Policy, personal dispositions and the evaluation of aircraft noise. *Journal of Environmental Psychology*, *31*(2), 147–157. doi: 10.1016/j.jenvp.2010.09.004

Letendre, S. E., & Kempton, W. (2002, feb). *The V2G concept: A new model for power? Connecting utility infrastructure and automobiles.*

Lipman, T. E. (2001). Grid-connected fuel cell vehicles as supplemental power sources.

In *Fuel cells and distributed generation planning conference, san antonio, texas* (pp. 1–9).

Lipman, T. E., Edwards, J. L., & Kammen, D. M. (2004). Fuel cell system economics: comparing the costs of generating power with stationary and motor vehicle PEM fuel cell systems. *Energy Policy*, *32*(1), 101–125. doi: 10.1016/S0301-4215(02)00286-0

Lo Prete, C., Hobbs, B. F., Norman, C. S., Cano-Andrade, S., Fuentes, A., von Spakovsky, M. R., & Mili, L. (2012). Sustainability and reliability assessment of microgrids in a regional electricity market. *Energy*, *41*(1), 192–202. doi: 10.1016/j.energy.2011.08.028

Magidson, J., & Vermunt, J. K. (2004). Latent class models. In *The sage handbook of quantitative methodology for the social sciences* (pp. 175–198). doi: 10.3102/0091732X010001305

Moncada, J. A., Park Lee, E. H., Okur, O., Chakraborty, S. T., & Lukszo, Z. (2017). Complex Systems Engineering : designing in socio- technical systems for the energy transition. , *3*(1), 1–13.

Mullan, J., Harries, D., Br??unl, T., & Whitely, S. (2012). The technical, economic and commercial viability of the vehicle-to-grid concept. *Energy Policy*, *48*, 394–406. doi: 10.1016/j.enpol.2012.05.042

Mwasilu, F., Justo, J. J., Kim, E.-K., Do, T. D., & Jung, J.-W. (2014, jun). Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration. *Renewable and Sustainable Energy Reviews*, *34*, 501–516. doi: 10.1016/j.rser.2014.03.031

North, D. C. (1991). Institutions. *The Journal of Economic Perspectives*, *5*(1), 97–112.

Olczak, B. M., & Piebalgs, A. (2018). *Sector Coupling: the New EU Climate and Energy Paradigm?* (Tech. Rep.). Florence: The Florence School of Regulation, European University Institute.

Oldenbroek, V., Verhoef, L. A., & van Wijk, A. J. (2017). Fuel cell electric vehicle as a power plant: Fully renewable integrated transport and energy system design and analysis for smart city areas. *International Journal of Hydrogen Energy*, *42*(12), 8166–8196. doi: 10.1016/j.ijhydene.2017.01.155

Open Power System Data. (2017). *Open Power System Data.* Retrieved 2017-10-30, from `https://open-power-system-data.org/`

Ostrom, E. (2011). Background on the Institutional Analysis and Development Framework. , *39*(1), 7–27.

Ottens, M., Franssen, M., Kroes, P., & Van De Poel, I. (2006). Modelling infrastructures as socio-technical systems Maarten Ottens , Maarten Franssen , Peter Kroes and Ibo van de Poel. *International Journal of Critical Infrastructure*, *2*(2), 133–145. doi: 10.1504/IJCIS.2006.009433

Park Lee, E. H., & Lukszo, Z. (2016, oct). Scheduling fuel cell electric vehicles as power plants in a community microgrid. In *2016 ieee pes innovative smart grid technologies conference europe (isgt-europe)* (pp. 1–6). IEEE. doi: 10.1109/ISGTEurope.2016.7856256

Park Lee, E. H., Lukszo, Z., & Herder, P. (2018). Conceptualization of Vehicle-to-Grid Contract Types and Their Formalization in Agent-Based Models. *Complexity*, *2018*, 1–11. doi: 10.1155/2018/3569129

Parsons, G. R., Hidrue, M. K., Kempton, W., & Gardner, M. P. (2014, mar). Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms. *Energy Economics*, *42*(0), 313–324. doi: http://dx.doi.org/10.1016/j.eneco.2013.12.018

Richardson, D. B. (2013a). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, *19*, 247–254. doi: 10.1016/j.rser.2012.11.042

Richardson, D. B. (2013b). Encouraging vehicle-to-grid (V2G) participation through premium tariff rates. *Journal of Power Sources*, *243*, 219–224. doi: 10.1016/j.jpowsour.2013.06.024

Rodatz, P., Paganelli, G., Sciarretta, A., & Guzzella, L. (2005). Optimal power management of an experimental fuel cell/supercapacitor-powered hybrid vehicle. *Control Engineering Practice*, *13*(1), 41–53. doi: 10.1016/j.conengprac.2003.12.016

Romeri, M. V. (2011). Considering hydrogen fuel cells powertrain as power generation plant. *World Electric Vehicle Journal*, *4*(1), 933–938.

Royal Netherlands Meteorological Institute (KNMI). (2015). *Uurgegevens van het weer in Nederland (Hourly weather data in the Netherlands) (in Dutch).* Retrieved from `http://knmi.nl/nederland-nu/klimatologie/uurgegevens`

Sahu, A. V., Park Lee, E. H., & Lukszo, Z. (2018). Exploring the potential of the vehicle-to-grid service in a sustainable smart city. In *2018 ieee 15th international conference on networking, sensing and control (icnsc)* (pp. 1–6). IEEE. doi: 10.1109/ICNSC.2018.8361289

Scholten, D., & Künneke, R. (2016, dec). Towards the Comprehensive Design of Energy Infrastructures. *Sustainability*, *8*(12), 1291. doi: 10.3390/su8121291

Shinoda, K., Park Lee, E., Nakano, M., & Lukszo, Z. (2016). Optimization Model for a Microgrid with Fuel Cell Vehicles. In *2016 ieee int. conf. networking, sensing and control (icnsc).* doi: 10.1109/ICNSC.2016.7479027

Simon, H. A. (1972). Theories of Bounded Rationality. In *Decision and organization* (pp. 161–176). doi: http://innovbfa.viabloga.com/files/Herbert_Simon___theories_of_bounded_rationality___1972.pdf

Smart Energy Demand Coalition. (2015). *Demand Response: Clarification of the standard processes required between BRPs and independent aggregators* (Tech. Rep. No. July 2015).

Sortomme, E., & El-Sharkawi, M. a. (2011). Optimal Charging Strategies for Unidirectional Vehicle-to-Grid. *IEEE Transactions on Smart Grid*, *2*(1), 131–138. doi: 10.1109/TSG.2010.2090910

Sortomme, E., & El-Sharkawi, M. a. (2012). Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Transactions on Smart Grid*, *3*(1), 351–359. doi: 10.1109/TSG.2011.2164099

Sovacool, B. K., & Hirsh, R. F. (2009, mar). Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. *Energy Policy*, *37*(3), 1095–1103. doi: 10.1016/j.enpol.2008.10.005

Thapar, V., Agnihotri, G., & Sethi, V. K. (2011). Critical analysis of methods for mathematical modelling of wind turbines. *Renewable Energy*, *36*(11), 3166–3177.

doi: 10.1016/j.renene.2011.03.016

Thomas, C. (2009, aug). Fuel cell and battery electric vehicles compared. *International Journal of Hydrogen Energy, 34*(15), 6005–6020. doi: 10.1016/j.ijhydene.2009.06.003

Tomić, J., & Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources, 168*(2), 459–468. doi: 10.1016/j.jpowsour.2007.03.010

Turton, H., & Moura, F. (2008, oct). Vehicle-to-grid systems for sustainable development: An integrated energy analysis. *Technological Forecasting and Social Change, 75*(8), 1091–1108. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0040162507002053` doi: 10.1016/j.techfore.2007.11.013

Uddin, K., Dubarry, M., & Glick, M. B. (2018). The viability of vehicle-to-grid operations from a battery technology and policy perspective. *Energy Policy, 113*(October 2017), 342–347. doi: 10.1016/j.enpol.2017.11.015

UK Department of Business Energy & Industrial Strategy. (2018). *Prices of fuels purchased by major power producers.* Retrieved 2018-04-20, from `https://www.gov.uk/government/statistical-data-sets/prices-of-fuels-purchased-by-major-power-producers`

US department of Energy. (2015). *Fuel cell technologies office* (Tech. Rep.). U.S. Department of Energy.

U.S. EIA. (2016). *Carbon Dioxide Emissions Coefficients.* Retrieved 2018-01-20, from `https://www.eia.gov/environment/emissions/co2{_}vol{_}mass.php`

USEF Foundation. (2015). *USEF: The Framework Specifications 2015.*

USEF Foundation. (2016). *USEF: Work stream on aggregator implementation models* (Tech. Rep.). Retrieved from `https://usef.energy/Upload/File/RecommendedpracticesforDRmarketdesign.pdf`

USEF Foundation. (2017). *Universal Smart Energy Framework (webpage).* Retrieved from `https://www.usef.energy`

Van Dam, K. (2009). *Capturing socio-technical systems with agent-based modelling* (Doctoral Thesis, Delft University of Technology). doi: uuid:1b36bc02-c7fe-4773-9ab2-3daa3b891754

Van Dam, K. H., Nikolic, I., & Lukszo, Z. (2013). *Agent-Based Modelling of Socio-Technical Systems.* Springer Publishing Company, Incorporated.

van Wijk, A. J. M., & Verhoef, L. (2014). *Our Car as Power Plant.* Retrieved from `http://www.iospress.nl/book/our-car-as-power-plant/`

Verzijlbergh, R. (2013). *The Power of Electric Vehicles: Exploring the Value of Flexible Electricity Demand in a Multi-actor Context* (Unpublished doctoral dissertation). Delft University of Technology.

Williams, B. D., & Kurani, K. S. (2007, apr). Commercializing light-duty plug-in/plug-out hydrogen-fuel-cell vehicles: "Mobile Electricity" technologies and opportunities. *Journal of Power Sources, 166*(2), 549–566. doi: 10.1016/j.jpowsour.2006.12.097

Williamson, O. (1979). Transaction-Cost economics: the governance of contractual relations. *Journal of Law and Economics, XXII, n. 2*(2), 233–261. doi: 10.1016/j.jcorpfin.2014.03.008

Williamson, O. (1998). Transaction cost economics: how it works; where it is headed. *De Economist*(1), 23–58.

List of Publications

S.S. Farahani, R. van der Veen, V. Oldenbroek , F. Alavi, **E. Park Lee**, N. van de Wouw, A. van Wijk, B. de Schutter , Z. Lukszo, *Hydrogen-based integrated energy and transport System: The design and analysis of the Car as Power Plant concept*, IEEE Systems, Man, and Cybernetics Magazine (2019)

E. Park Lee, Z. Lukszo, P. Herder, *Aggregated fuel cell vehicles in electricity markets with high wind penetration*, 2018 IEEE International Conference of Networking, Sensing and Control (ICNSC) (2018)

A.V. Sahu **E. Park Lee**, Z. Lukszo, *Exploring the potential of the vehicle-to-grid service in a sustainable smart city*, 2018 IEEE International Conference of Networking, Sensing and Control (ICNSC) (2018)

E. Park Lee, Z. Lukszo, P. Herder, *Conceptualization of vehicle-to-grid contract types and their formalization in agent-based models*, Complexity, pp. 1–11 (2018)

E. Park Lee, Z. Lukszo, P. Herder, *Static volume-based and control-based contracts for coordinating vehicle-to-grid supply in a microgrid*, 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe) (2017)

J. Moncada, **E. Park Lee**, G. Nava Guerrero, O. Okur, S. Chakraborty, Z. Lukszo, *Complex Systems Engineering: designing in socio-technical systems for the energy transition*, EAI Endorsed Transactions on Energy Web (2017)

F. Alavi, **E. Park Lee**, N. van de Wouw, B. de Schutter, Z. Lukszo, *Fuel cell cars in a microgrid for synergies between hydrogen and electricity networks*, Applied Energy, **192** pp.296 – 304 (2017)

E. Park Lee, Z. Lukszo, *Scheduling Fuel Cell Electric Vehicles as power plants in a community microgrid*, 2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe) (2016)

K. Shinoda, **E. Park Lee**, M. Nakano, Z. Lukszo, *Optimization model for a microgrid with Fuel Cell Vehicles*, 2016 IEEE International Conference of Networking, Sensing and Control (ICNSC) (2016)

Z. Lukszo, **E. Park Lee**, *Demand side and dispatchable power plants with electric mobility* in *Smart grids from a global perspective: Bridging old and new energy systems* A. Bealieu, J. de Wilde, and M.A.J. Scherpen, Eds., Springer International Publishing, pp.163 – 177 (2016)

E. Park Lee, E. Chappin, Z. Lukszo, P. Herder, *The Car as Power Plant: Towards socio-technical systems integration*, 2015 IEEE PowerTech, pp.1 – 6 (2015)

Curriculum Vitae

Esther Hae-Kyung Park Lee was born on the 4th of February 1986 in Barcelona, Spain. After finishing her high school education at the Kensington School of Barcelona she started her bachelor studies in the same city. In 2009, she received a bachelor degree in Chemical Engineering from the Institut Químic de Sarrià, Universitat Ramon Llull.

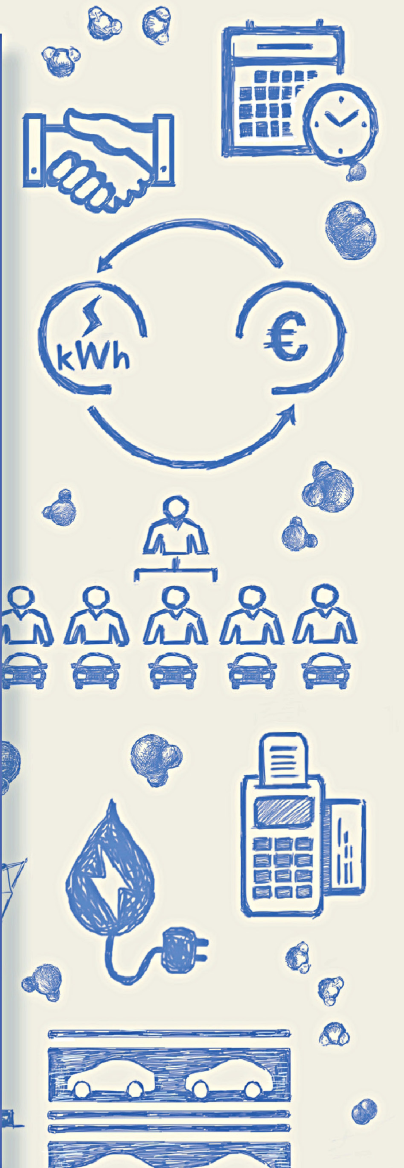
After a year of work experience in the agri-business sector, she moved to the Netherlands to pursue a master degree in Industrial Ecology. In 2013, she received her degree after successfully defending her master thesis on *"Combining theories and techniques to model the decision-making behavior of homeowners: Formalization of an agent-based model to study the adoption and diffusion of solar PV systems in the Netherlands"*.

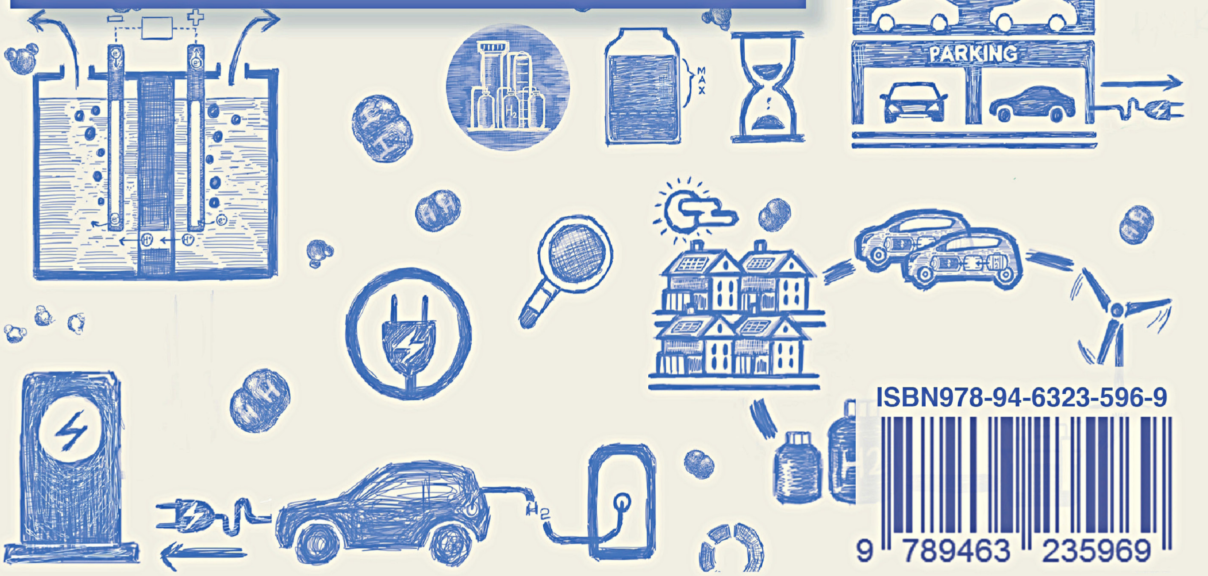
In 2014, she started as a PhD candidate at the Energy & Industry group in the Faculty of Technology, Policy and Management of the Delft University of Technology. Throughout the duration of her PhD, she assisted in a bachelor course on agent-based modeling (2015, 2016) and supervised three master thesis projects and one bachelor project (2014-2018). Moreover, she was involved in the organization of the group's weekly Power Rangers meetings in 2017. Her PhD was part of the multi-disciplinary project *Car as Power Plant (CaPP) - Fuel cell cars creating an integrated, efficient, reliable, flexible, clean, multi model and smart transport and energy system* (2014-2018) within the NWO URSES program. She used the socio-technical system operation framework to analyze CaPP systems and conceptualized contract types for vehicle-to-grid with fuel cell electric vehicles. Furthermore, she built two agent-based models to test and explore the role of contracts in the operation of two CaPP system examples. Throughout the research, she presented her work in several international conferences and also shared some of her insights in a mini-lecture for a massive open online course (MOOC) on electric mobility and policy. Her research culminated in her PhD thesis *"A socio-technical exploration of the Car as Power Plant"*. Collaboration with members of the CaPP project also resulted in the publication of two journal papers.

The Car as Power Plant (CaPP) system is based on the idea of increasing the use of renewable electricity using hydrogen as an energy carrier and fuel cell electric vehicles (FCEVs) as flexible power plants. The use of FCEVs as paower sources introduces a novelty in the physical system and it involves new actors and roles: car drivers that act as prosumers, and aggregators that trade the energy from aggregated vehicles. This introduces the need for new institutions (rules) to manage the transactions.

This thesis explores the role of institutions in the management of vehicle-to-grid transactions in Car as Power Plant systems. The operation of CaPP systems are modeled as a combination of the physical system operation, actions of involved actors, and the rules governing their actions and interactions. To engage heterogeneous drivers in different types of vehicle-to-grid participation, three distinct sets of rules are conceptualized as volume-based, control-based and price-based contracts. The influence of these rules in the system is tested through simulation experiments with two agent-based models. The results show the profound impact of these rules on the system performance.

This work demonstrates the importance of analyzing innovative technologies with a socio-technical system perspective. Moreover, it provides crucial insights in the complexities of bringing innovative technologies into being.





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