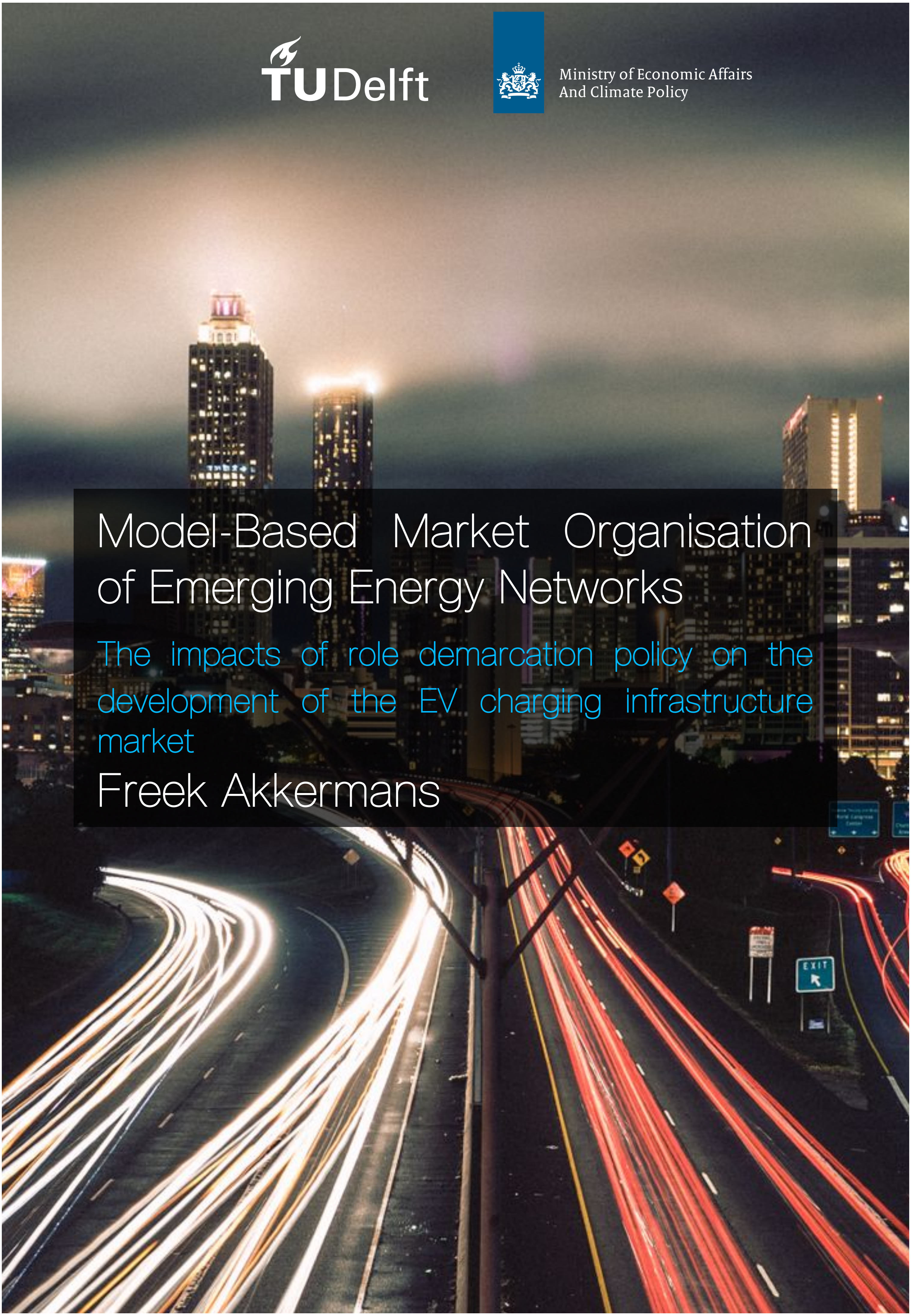

Ministry of Economic Affairs
And Climate Policy

Model-Based Market Organisation of Emerging Energy Networks

The impacts of role demarcation policy on the development of the EV charging infrastructure market

Freek Akkermans

Model-Based Market Organisation of Emerging Networks

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by

Freek Akkermans

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Executive Summary

The global trends towards sustainable energy systems characterise the energy sector by rapid changes. The high innovation rates caused by this transition result in frequent emergence of new markets within and related to the energy sector. Serving a fundamental facilitating role, network companies are challenged by these developments because new markets or products often come with new demands for infrastructure. Network companies respond to these challenges by expanding their activities by entering new energy infrastructure markets such as hydrogen infrastructure, storage, and the electric vehicle charging infrastructure market. This expansion is mainly driven by the desire to increase their control over the system and by synergy motives due to the unique position of a network company.

A network company is a holding company with a distribution system operator (DSO) in the group. Since energy infrastructure is a natural monopoly, the regulatory framework is aimed at allowing legal monopolies on these infrastructure markets while preventing possible market disruption as a consequence. In the Netherlands, this is done by price regulation and role demarcation policies: a DSO is the only party allowed to build and maintain the electricity and gas distribution networks within its designated region, but its performance is monitored and regulated and the networks are unbundled from other markets in the supply chain such as production and sales. A network company is formally defined as a private company, but because of the presence of a DSO in the group they are assigned a special status to make sure that no special advantages should be transferred from and to the market party that owns the network.

The mentioned developments create a difficult situation from a regulatory perspective: network companies want to expand their activities and stimulate the development of the market while their unique market position might cause them to disrupt the future development of that same market. A first sensitive situation arose in the Netherlands when network company Alliander entered the electric vehicle (EV) charging infrastructure market. While from one perspective many benefits were expected, others argued that their position creates unfair competition compared to regular market parties. The development of the discussion highlighted the presence of many grey areas and unknown impacts of role demarcation policy on new infrastructure markets. Supported by the desire of the regulator to make decisions on role demarcation policy earlier in the market development process, the following question arises:

How does role demarcation policy influence the development of the electric vehicle charging infrastructure market in the Netherlands?

The fundamental problem owner for this research is the responsible party for demarcating the roles on the infrastructure markets: The Ministry of Economic Affairs & Climate Policy. The aim is to answer the research question by specifically focusing on long-term dynamics and uncertainties related to the new electric vehicle charging infrastructure market. The research approach is Exploratory System Dynamics Modelling and Analysis, and the time period is taken from the emergence of the market in 2010 until two complete life-cycles of a typical EV charging station later at 2030. As a foundation for the exploration of the system, a System Dynamics (SD) model of the EV charging infrastructure market is built with regard to existing literature and expert consultations about the structure and the functioning of the EV charging infrastructure market development system.

Since the problem concerns market development, a behaviour based approach has been taken: simulated market development outcomes are analysed through sensitivity analysis on multiple moments in time and by behaviour based scenario discovery. The sensitivity analysis is done by variance decomposition by calculating Sobol indices on various moments in time. By doing so, the development of the sensitivity of the model outcomes of interest is measured. For behaviour based scenario discovery, time series clustering has been used: of the complete ensemble of time series outcomes, the ensemble is partitioned into a suitable number of clusters by applying a time series clustering algorithm on the dataset. For each cluster, corresponding cluster predictors have been analysed in order to induce generative rules concerning input-output

influences. The combination of these methods provide an elaborate understanding of the modelled system's behaviour over time, representing the EV charging infrastructure market development over the given period. Finally, all research findings have been discussed comprehensively with policy experts from the Ministry of Economic Affairs & Climate Policy and the Ministry of Finance.

Differences in investment behaviour between commercial parties and network companies, the vehicle market, and EV charging infrastructure market specific dynamics drive the variation of the market outcomes. The model is therefore based on an SD supply-demand-price concept and is further expanded using 3 different structures: vehicle development, electric vehicle charging stations (EVCS) supply, and market party investment behaviour. Access to financial capital, risk valuations, and profit targets are identified as main drivers for investment behaviour differences. The dynamics driven by external factors and uncertainties that influence the system are vehicle development, cost reduction learning curves, and technology development learning curves. The key performance indicators for market development are price development, entrance barriers and demand satisfaction of which the critical entrance barriers are found to be cost advantages and capital requirements. The price is measured by taking the added charging fee per kWh, the cost advantages are measured by calculating the differences in capital expenditure for new projects between the different market parties, demand satisfaction is measured by taking the number of public EVCS relative to the number of EV's on the vehicle market, and capital requirements and market attractiveness is analysed by measuring the expected returns on investment of commercial parties when maintaining marginal prices. The resulting model has been validated through face validity and comparison with existing research outcomes and models.

Both the sensitivity analysis and behaviour based scenario discovery showed a difference in short-term (2010-2020) performance and long-term performance (2020-2030), where behaviour and values were considerably consistent within these separate periods. An important distinction is thereby made between short- and long-term performance and several trade-offs have been identified.

Concerning the feedback effects between the charging infrastructure and the vehicle market, the results have shown that when the demand for public charging stations is satisfied, the EV infrastructure market development does not influence the BEV market. Additionally, in all simulated scenarios the charging infrastructure demand is satisfied, allowing no certain statements on completely discarding feedback effects from the charging infrastructure market but also indicating satisfying and sufficiently following market development behaviour. Other market dynamics in the system however have much stronger influences on the system: larger investment behaviour differences between network companies and commercial parties result in lower prices, but market attractiveness is significantly disrupted as well. Economies of scale and technology development effects tend to amplify these consequences increasingly over time.

From the various policies that have been implemented, the shareholder activation is concluded to be ineffective. Setting a certain market entry period, as is currently done by using temporary activity measure, has only little effect on the attractiveness of the market: the outcome space becomes more robust and ensures at least the possibility for commercial parties to break-even when investing on the public EVCS market. The temporary task is therefore considered to be successful in fulfilling its intended purpose, but its limited effect should be considered when deciding to use the instrument. Other factors such as process costs and possible effects on stakeholder relations may outweigh the eventual effect of the policy measure on the market.

The most effect policies are complete restriction of network companies on the market or setting a maximum market share for network companies. Setting a low market share cap or restricting entry for network companies lowers market entrance barriers and increases attractiveness of the market for commercial parties, but estimated charging fees will develop towards higher prices. On the long-term, the EV charging fees outcomes are additionally heavily influenced by market specific cost reducing dynamics. The most influential policy measures should therefore be aimed at directing the market development on the short-term only, and additionally create a challenging dilemma for the decision-maker who is forced to prioritise desired market outcomes. Adding to the complexity of the dilemma, the trade-off between price development and commercial party profitability is in line with a most relevant issue on the subject of energy policy: the tension between free market theory and the more technical system perspective. Lower prices indicate a more efficiently functioning system resulting in cost-efficient production, and more profitability for commercial parties increases the attractiveness of the market for commercial parties which increases fair competition. Network companies typically favour optimisation of the system, and the Ministry of Economic Affairs and Climate Policy generally strives for free market scenarios. In an attempt to aid further decision-making with respect to this dilemma, an important nuance is added through the research findings: price development differences are much larger than profitability differences and significant effects of underlying uncertain market dynamics are considerably little on the short-term. In developing a certain strategy, this implies two very important considerations:

1. *Negative effects of restricting or limiting access on the market for network companies on price development are much larger than the positive effects on profitability.*
2. *The most significant and uncontrollable effects of uncertainties occur after a considerably long period of time, granting the decision-maker the opportunity to adjust previous decisions when more accurate predictions can be made due to presumably increasing availability of historical and empirical data.*

Finally, the presented findings raise probably the most important question of all: "Should we implement role demarcation policy on an emerging market?". Within the boundaries of this research, this question cannot unambiguously be answered. However, the results do contribute towards finding the answer to this question is: Limiting or restricting activities of network companies on the market moderately affects short-term market development. The first period of a market development cycle is generally the most decisive period for shaping total results and the decision-maker should therefore focus on the short-term effects, prioritise the outcomes of interest, and thereby select an appropriate course of action. When prioritisation is impossible or a balanced dilemma still remains after prioritisation, this might imply that implementing no policy at all would actually be the most suitable action.

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List of Abbreviations

ACM - Consumer & Market Authority (Authoriteit Consument en Markt)
AIR - Aggregated Investment Responsiveness
BEV - Battery Electric Vehicle
CAPEX - Capital Expenditures
CBS - Statistics Netherlands (Centraal Bureau voor de Statistiek)
CID - Complexity-Invariant Distance
CLD - Causal Loop Diagram
CORT - Combined Temporal Correlation and Raw Values
CPB - Netherlands Bureau for Economic Policy Analysis (Centraal Planbureau)
DSO - Distribution System Operator
DWT - Discrete Wavelet Transform
EA&CP - (Ministry of) Economic Affairs and Climate Policy
ED - Electricity Demand
EMA - Exploratory Modelling & Analysis
ESDMA - Exploratory System Dynamics Modelling & Analysis
EV - Electric Vehicle
EVCS - Electric Vehicle Charging Station(s)
GSA - Global Sensitivity Analysis
ICE - Internal Combustion Engine(s)
IEA - International Energy Agency
KPI - Key Performance Indicator
kWh - Kilowatt Hour
LHS - Latin Hypercube Sampling
LIC - Levelised Investment Cost
MP - Market Price
MS - Market Share
NWC - Network Company
OPEX - Operational Expenditures
PBL - Netherlands Environmental Assessment Agency (Planbureau voor de Leefomgeving)
PHEV - Plug-in Hybrid Electric Vehicle
PI - Profitability Index
RAND - Research and Deployment (Corporation)
ROI - Return on Investment
ROIA - ROI aim
RVO - Netherlands Enterprise Agency (Rijksdienst voor Ondernemened Nederland)
S1 - First order Sobol Index - Main effect
S2 - Second order Sobol index - Interaction effect
SD - System Dynamics
ST - Cumulative Sobol index - Total Effect
TP - Target Price
VET - Energy transition progress ((Wet) Voortgang Energie-Transitie)

1 Introduction

1.1. Research background

1.1.1. The DSO, the naturally legal monopoly and the unbundling of electricity networks

Energy infrastructure is a natural monopoly. Due to large fixed costs, a homogeneous product, and strong economies of scale benefits, a single seller can serve the entire market at the downward sloping section of the average cost curve (Helm, 2002). Recognizing these characteristics of the market has led Europe towards not just allowing monopolists on the market, but to assign certain parties to specific tasks and regions as well. In the Netherlands, fundamental energy infrastructures (primarily electricity and gas) are legally divided among these Distribution System Operators (DSO's) by region (Jamasb and Pollitt, 2005). This position grants the DSO the opportunity to efficiently operate, but it also increases its market power. To prevent harmful opportunistic behaviour, these legal monopolists are regulated: because of possible conflicts of interest or unfair competition networks are unbundled from production and DSO's are regulated on price levels (ACM, 2018; Künneke and Fens, 2007). Additionally, the Dutch regulatory design means no high investment risks and cost-regulation results in safe profits, to ensure DSO reliability and security of the network operations as a fundamental utility sector (ACM, 2015; Braeutigam and Panzar, 1989).

When the Electricity law in 1998 and the Gas law in 2000 went into effect, providing market and regional boundaries, unbundling rules, financial guidelines, and role definitions. An important detail of these last definitions is a nuance in the unbundling rules: the DSO is allowed to be part of a holding, but not when there are other network operators, suppliers, or production companies in the group. No expropriation or comparable interventions in ownership relations between the DSO and its owners were therefore made mandatory. However, the parties were insisted to "raise such a high wall" between the market parties and grid management that the DSO is completely independent in its daily operations. While formally private parties, these holdings have a special status because of the presence of a DSO in the group. The holdings are defined as Network Companies (NWC's) and the electricity law states that although a reasonable profit may be paid out, no special advantages due to cash flow, capital position or information transfer should be transferred from and to the market party that owns the network (Wijers, 1997). This means that cross-subsidisation between members of the group is not allowed and favouring in any form is forbidden. Additionally, to preserve public interest and to enable public supervision, the stakeholders of the holding are Municipalities and Provinces (van der Hoeven, 2008).

1.1.2. A continuously changing energy sector and emerging new markets

The ongoing energy transition has become an unmistakable part of our future: a trend towards a sustainable energy system is present and the sector is characterized by rapid changes (Foley and Olabi, 2017; Jefferson, 2006; Uzun, 2002). Whether centralized or decentralized, the rising desire for alternative, renewable technologies drives parties towards high innovation rates. Consequentially, this innovation climate results in a frequent emergence of new markets (Araújo, 2014; Magnusson and Berggren, 2018; Rhys, 2016). The characters of these markets vary a lot and many have significant impacts on the energy infrastructure: renewable energy technologies create challenges concerning electricity network balance, large scale electric vehicle usage means more electricity demand but provides opportunities for innovative balancing mechanisms, and many aggregating roles arise on the borders between users, producers and the grid operators (Mathiesen et al., 2015; San Román et al., 2011; Zhang et al., 2014). These bordering areas are new and increasing in numbers, and in many cases create grey areas concerning market role demarcations.

Renewable energy sources and increasing electricity demand means increasing pressure on a grid operator because of unknown developments and uncontrolled inputs on the networks, while having the legal obligation to provide. Since a network company serves a utility function and its activities typically facilitate other markets, synergistic effects are frequently found when combining its activities with operating on related markets (Huang et al., 2012; Zhang et al., 2014). The network companies desire innovation and regularly find opportunities which may benefit from the expertise of a network company, and in its turn may benefit the network operator by balancing the network or simply providing more control over the activities on the network. However, when the desire is greater than the actual realisation of a certain product or service, a lack of faith in the development of the market is present. As a private holdings with a grid operators within their groups, network companies then typically show much interest in these new markets, sometimes even start operating on them alongside independent commercial market parties (Don, 2017; Kleijne, 2014; Nederland, 2017).

1.1.3. Market complications and the increasing complexity of role demarcation

In the Dutch energy sector, network unbundling, price regulation and the supply obligation policies demarcate the role of a DSO very strictly. The role of a network company is also demarcated, but less strict (section 2.1.1.). A proper demarcation is essential because in various cases, the network company can be an unequally powerful party on a market and its presence may disrupt the market (Nardi, 2012; Wiebes, 2018). The characteristics, means, and knowledge of network companies could however also create possible positive effects like economies of scale or synergistic effects, which may outbalance the negative impacts (Künneke and Fens, 2007; Świerczek, 2014).

While excluding a commercial activity from a public task that should or does belong with the DSO is manageable, it is very difficult to determine whether an activity should belong to a network company. Due to the complex idea of a network company, the definition of a task that should belong to a network company remains quite vague: the activities of a network company must be non-disruptive, sufficiently network-related, and societal benefits must outweigh societal costs. An activity being sufficiently network-related is a very subjective statement, leaving the non-disruptive and societal cost and benefits balance as important, somewhat measurable criteria. However, to do this, the development of a market must be estimated. The development of an emerging market is difficult to predict: The factors that determine the development are uncertain due to a lack of historical data and market development is a typically dynamic process (Deszca et al., 1999). For this reason, current role demarcation policies have been formed in hindsight: a pragmatic process led by observed, mostly undesired experiences (interviews Ministry of EA&CP and ACM: Appendix A).

There is one thing that all parties (commercial parties, network companies, and the regulator) agree upon: the role of the network company is unclear and should be clarified (interviews: Appendix A). Current laws are generally considered to provide incomplete definitions and therefore role demarcations are currently being discussed in relation to the "Energiewet 1.0", the new energy law under development that is aimed at updating and combining current Dutch energy laws (Wiebes, 2018). However, there is a lot of discussion on how to shape the law, from what angle the law has to be defined, and how strict the demarcations should be (ACM, 2017a; IPO, 2018). The only consensus that is clearly found on the subject is that clarification of these roles is necessary.

1.1.4. The case of electric vehicle charging infrastructure

The very general market demarcation problems have been highlighted by a specific case concerning EV charging infrastructure. Alliander, one of the 3 largest Network Companies in the Netherlands, has shown interest in EV markets since about 2007, which developed in 2013 into a single subsidiary company within the holding: Alliander Mobility Services, which was renamed to Allego shortly after its founding (Alliander, 2014). Allego was one of the first parties that aimed at implementing EV charging infrastructure on a larger scale, along with commercial companies The New Motion, Fastned, Mister Green & Greenflux. At that moment, the EV charging business case was strongly criticized and the involved companies were referred to as 'believers' rather than visionaries (Kleijne, 2014). The classification of the companies by the public points out the novelty on the business case and as a consequence the EV charging market typically developed slowly. The slow development combined with the expected benefits for Liander (the DSO in the Alliander group) that may follow by gaining knowledge about the impacts of electric transport on the electricity network and its consumers were the fundamental reason for Alliander to found the venture (Kleijne, 2014).

Since the EV charging market was not yet developed as desired, Allego was operating separate from Liander, and because there is a societal benefit from the development of the market, the ACM or the Ministry of Economic Affairs was not necessarily triggered to investigate the situation. It can be said that the activity was a positive developed at that moment and there was no reason perceived to intervene (interview Ministry of EA&CP: Appendix A). The main reasons for allowing the NWC to "push" the market was the general desire to stimulate the development of BEV attractiveness as a personal transport vehicle: BEV range is a strong driver of the potential the market penetration of full electric vehicles and increasing charging utilities availability and performance increases the cumulative range for BEV users (Chan and Wong, 2004; Dimitropoulos et al., 2013; Namdeo et al., 2014).

Since Allego is operating on a commercial market, the discussion slowly arises whether this is right of not. In 2015, RWE requested an investigation from the Consumer & Market Authority (ACM) because they claimed to be experiencing unfair competition because of the market power and public income sources of Alliander. According to RWE, Allego was operating on a strictly commercial market which a Network Company was not allowed to and should cancel all activities, with that they pointed out the law on independent system operation (Duijnmayer, 2017b). In 2016 ACM concluded that they found insufficient reason to enforce this because Allego's activities would be sufficiently related to electricity infrastructure (ACM, 2016).

The intensified problems around the EV charging case now did trigger the regulator and the Ministry of Economic Affairs and Climate Policy created the "energy transition progress law (Wet Voortgang EnergieTransitie, Wet VET)", which clarifies guidelines regarding what kind of activities are allowed by a network company and introduces the concept of a temporary activity. The law restricts the ability of a network company to enter a market on its own and enables the regulator to allow a network company to undertake a certain activity for a limited time period (Kamp, 2017). However, the new law yet leaves some grey areas because the boundaries of the restrictions and the illustrated process to determine whether the temporary activity should be allowed for a network company is not clear or not suitable (Interviews: Ministry of EA&CP: Appendix A). The discussion develops even further, varying from encouraging the innovative initiative from a public aspect to strong critique against Allego's rapid expansion. In 2017, Essent and Nuon formally appealed the court to review the earlier ACM judgement and the electricity law. The main argument was that the ACM should've considered the upcoming "Wet VET" that was being developed. Fastned and The New Motion entered the discussion as well and arguments were expanded to the accusations that Allego would be competing with tax money and the possible synergistic effects argument would have become irrelevant because Allego was already operating far beyond the operational area of Liander (Bremmer, 2017; Duijnmayer, 2017b; Kapital, 2017; van Mersbergen, 2017). Many court processes concluded in partial illegal activities by Allego, but not necessarily meant that Alliander should exclude Allego from the group and implied at most that Allego should slightly adjust their processes (Duijnmayer, 2017a; Hylkema, 2017).

In 2018, Alliander puts Allego up for sale. According to Alliander, the subsidiary should expand to maintain a strong market position, but the perceived investment risks are too high which doesn't fit within the profile of a network company. Several months later, Allego was sold to Meridiam, a French investor specialized in development, finance and maintenance of sustainable infrastructure projects (Alliander, 2018a; van Dijk, 2018; van Heerde, 2018).

1.1.5. The problem owner: Ministry of Economic Affairs & Climate Policy

The problem owner for this research is the responsible party for demarcating the roles on the energy infrastructure markets: The Ministry of Economic Affairs and Climate Policy (EA&CP). More specifically, section networks management of the department of Climate and Energy Policies. The problem owner is currently investigating options to address the increasing possibility of problems of market activity of a NWC on a new market. Stakeholders do not agree upon the effects and possible future outcomes, or don't agree on how these effects compensate each other (ACM, 2017b; Bremmer, 2017; Fennema, 2018; IPO, 2018; Nederland, 2017; Wiebes, 2018). There is a desire for clarity on market roles for NWC's. Market parties aim at the Ministry of

EA&CP for providing this clarity (interviews Ministry of EA&CP, Alliander, Enexis, and ACM: Appendix A).

The new Energiewet 1.0 is currently being developed to update and combine the former Elektriciteitswet and the Gaswet. The Ministry aims to use this opportunity to further formulate clear market roles, specifically aiming at stimulating high market concentrations and market development. However, since role demarcation policy is typically made by responding to observed market developments, expertise and tools are missing to unambiguously determine future based long-term policy (Wiebes, 2018) (interviews Ministry of EA&CP).

1.2. Research gaps

The energy transition is continuously changing the energy sector and a high innovation rate results in new markets emerging constantly. Emerging, undeveloped markets are susceptible to a significant portion of uncertainties, for the long-term effects are yet to be discovered. Various theories creating these uncertainties can be identified, however research on the effects of uncertainties on market development in general are limited and research on possible effects of certain market characteristics on the long-term are found to be driven solely by assumptions concerning the "values" of these characteristics. For energy infrastructure markets, theoretical research dominates the domain and as found in section 1.1 contributes by suggesting certain dynamic concepts to have certain effects when specific market characteristics are assumed. What is missing however, is knowledge and insights about how these different assumptions impact the system. This presents the first knowledge gap:

Research gap 1: There is a lack of consideration of the effects of uncertainties on the development of new energy infrastructure markets.

The Ministry of EA&CP is increasingly being addressed by market parties to react upon the activities of network companies on different new and underdeveloped markets that are, according to the network companies itself, related to the core tasks of the holding. An intense discussion has risen throughout the years with different market parties and governmental organisations being unable to agree with each other on the impacts of certain role demarcation policies. The most recent initiatives such as the Wet VET or the general concept of a temporary activity have been both encouraged and rejected by stakeholders. The problem lies with the large availability of theoretical concepts that can be related to the subject: a series of valid arguments can be made for each point of view. The challenge is to be able to compare the effects of different concepts and to provide insights regarding a synthesized balance or the interactions between these dynamics. From the regulator's perspective, this gives us a second knowledge gap:

Research gap 2: There is a lack of synthesized comparative research on the impacts of market party role demarcations on the short- and long-term market development of new energy infrastructure markets.

1.3. Research goal

The main research goal is to analyse the influences of specific role demarcation policies on the market development of energy infrastructure markets. Specifically, electric vehicle charging infrastructure will be addressed as a case study. The research will intentionally be performed from an aggregated perspective to support the possibility to use the obtained insights as a reference for similar cases. The main research question however remains as follows:

How does role demarcation policy influence the development of the electric vehicle charging infrastructure market in the Netherlands?

The answer to this question is not as straightforward as it appears. The EV charging infrastructure market is an emerging market, with many uncertainties influencing market development. The uncertainties complicate the decision-making process significantly because key aspects of the system's structure are unknown which makes it difficult to make assumptions regarding the effects on the long-term. It is therefore essential to know how uncertainties can influence the system, how they interact with each other and with policy measures, and to know how sensitive outcomes of interest are to both the uncertainties and policy implementations. The answer to this question is in this research attempted to be found by answering the following sub-questions:

1. How can the EV charging infrastructure market development process be conceptualised?

The first task is to create a full understanding of the critical aspects of the EV infrastructure market. Performance indicators should be defined, general sources for uncertainty must be identified, and the critical structures that are most decisive for the market's development should be selected. Since market development is a very wide definition, the market development concept should also be conceptualised and a clear, unambiguous definition must be formulated. Using these insights, the system will be conceptualised in terms of inputs, outputs, and underlying system relations.

2. How can the conceptualised market development process be formalised into terms of inputs, relations and measurable outcomes?

Following up on the conceptualisation, a modelling and simulation approach is proposed. A quantitative modelling approach provides the opportunity for generating clear, measurable outcomes which supports the ability to compare various scenarios. The conceptualised structures, uncertainties and metrics of interest will thus further be developed into measurable variables and interactions which together describe the EVCS market development system. Uncertainties will be defined as variable parameters, metrics of interest are the measurable factors that are monitored throughout the entire analysed period, and structures will be defined by quantifying the relations and interactions of the variables in the model.

3. What are the effects of uncertainties on the possible future behaviour of the EV charging infrastructure market development system?

To understand the market development of EV charging infrastructure, the formalised model must be analysed comprehensively. Without yet adding any policy implementations, this will show how (in)sensitive the market development performance indicators are to the uncertainties. Additionally, this illustrates the reference outcomes of the EVCS market development, which is essential for further policy analysis.

4. What are the effects of policy interventions on the possible future behaviour of the EV charging infrastructure market development system?

Finally, policy options will be implemented and their effects on the system will be analysed. Again, similar to the previous part, the (in)sensitivity of the market development performance towards uncertainties will be analysed, but now focused on how policies influence this sensitivity. A policy can be effective either when it increases insensitivity of the outcomes towards uncertainties or when it positively affects certain outcome values.

Finally, the answers to all questions combined will provide the answer to the main research question. The impacts of different policy implementations are clear and a general understanding of possible market development paths is created. The answer to the main question will also provide a basis for formulating policy advise for the Dutch Ministry of Economic Affairs and Climate Policy on how to cope with emerging energy infrastructure related markets from a role demarcation perspective.

2
Methodology

This chapter presents the research methods that are used in the research. The sections are separated by method, with a final section to present the conclusive research framework.

2.1. Literature study & expert consultation

To conceptualize the system, relevant literature will be studied and experts will be consulted. While these are two very common processes, to specify the means for this part, a brief description of the exemplary sources is presented:

Literature research:

- Governmental documents: From legal texts to ministerial correspondence, relevant to the subject. All publicly available.
- Opinion papers of stakeholders: ACM, Netbeheer Nederland, Direct market parties, etc.
- Scientific papers: Investment behaviour modelling, market economics, EV charging infrastructure business models.
- National data: CBS-, CPB-, RVO-, and PBL-data and reports.
- International data and trends: IEA- and Bloomberg-data and reports.

Another highly effective source of information on the subject is to derive information from expert consultations. The term expert consultations is used here as a aggregated reference to all sorts of stakeholder insights. A short, general list of the organisations related to the experts that have been spoken with:

Expert consultation:

- Ministry of Economic Affairs and Climate Policy
- Ministry of Finance
- Alliander & Enexis group (Network Companies)
- Liander & Enexis (DSO's)
- Consumer and Market Authority (ACM)
- Eneco (Energy supplier)
- Limburg Province (Shareholder)
- Netbeheer Nederland (Representative body for all DSO's and NWC's)
- Cogas/Coteq Netbeheer
- TU Delft

2.2. System Dynamics

A market development process as presented in this research is a highly dynamic process. Possible development paths are shaped by underlying processes that can have enforcing, mitigating or even reversing effects on the system's outcomes. Because of these dynamics and expected non-linear behaviour of the electric vehicle charging infrastructure development system, System Dynamics (SD) is used to model the system. SD is a computer-aided approach specifically aimed at policy analysis and design. It applies to dynamic problems arising in complex social and economic dynamic systems characterized by interdependence, mutual interactions, feedback, and circular causality (Forrester, 1994). Hence, SD is considered to be a suitable method in describing the EV charging infrastructure market development system.

SD models are in essence large sets of integral equations which are numerically solved by following numerical integration methods (Forrester, 1994). An SD-model typically consists of constants, auxiliary functions, flow functions and stocks. A characteristic element of SD models are stocks, where the behaviour of a stock over time is defined as an integral equation. These structures make SD a suitable medium for modelling systems that are dominantly shaped by feedback effects, delays, and accumulations with non-linear behaviour (Kwakkel and Pruyt, 2015). Additionally, SD allows to focus on dynamics over time instead of just end-states, enabling one to assess the continuous development of a system.

The base model will be made by means of System Dynamics, which will then be explored extensively. Note that the SD-model will be used to formalise essential structures of the system for exploratory purposes and is in this research not meant to be used to achieve accurate predictions of how the market will specifically develop, but rather to find trends and correlations in the entire ensemble of possible future scenarios.

2.3. Deep uncertainty

The development of emerging markets is typically characterized by uncertainties. As highlighted in Chapter 1, the main problem of the issue is the inability to estimate market development of new markets because of yet remaining uncertainties regarding market characteristics. In order to analyse the possible processes integrally, uncertainty must be taken into account. To properly understand the notion of uncertainty, the conceptualization of "deep uncertainty" by Lempert, Popper, and Bankes (2003) has been used for this research:

"...that is, where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes."

This notion explicitly applies on decision-making problems. This idea of deep-uncertainty will throughout the research be used to identify uncertainties in the development system and to estimate market development under these uncertainties.

2.4. Exploratory Modelling and Analysis

To model and analyse system dynamics under deep uncertainty, a certain approach must be taken. Exploratory modelling and Analysis is an approach that uses computational experiments to analyze complex systems under a range of specified uncertainties. Developed by the RAND Corporation, EMA aims at offering decision support while dealing with a wide range of irreducible uncertainties by systematically exploring the consequences of these uncertainties. More specifically, combining EMA and SD enables the researcher to study all plausible dynamics of a complex system over time. This combination of methods is referred to as 'exploratory system dynamics modelling and analysis' (ESDMA) (Kwakkel and Pruyt, 2013, 2015) and will be applied in this research.

Fundamentally, conceptualisation of the system will be done by following the XLRM-framework by Lempert (2003). The framework structures the model in terms of exogenous uncertainties outside the control of decision makers (X), policy levers or near term actions (L), causal system relations (R) and metrics of interest (M). Where X and L are inputs for the model, M are the outputs and R represents the model structure itself. Following on this conceptualisation, computational methods can be applied to the model when identifying all XLRM components. In this research, the methods chosen are aimed at sensitivity analysis and scenario discovery.

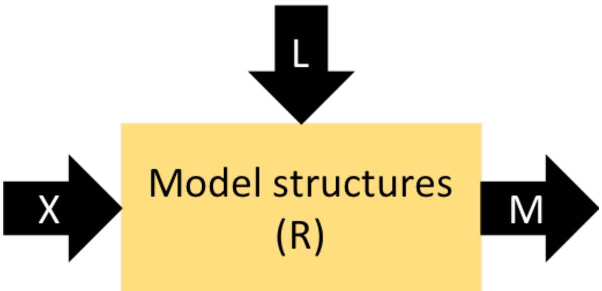


Figure 2.1: An illustration of the XLRM concept by Lempert (2003).

The goal is to find the answers to what basically is a vast amount of what-if questions and to draw conclusions from all generated outcome situations. This also means that the projections and the outcome ensemble are not suitable for making statements about the likelihood of certain outcomes to become real, but can be used to deduce structural effects of policies and uncertainties on the behaviour of the model's entire outcome ensemble.

2.4.1. Sensitivity analysis: Variance based Sobol indices

Sensitivity analysis examines the variance in outputs related to the variance in inputs to determine what the level of influence of all inputs on the outputs (Saltelli and Annoni, 2010). This is used to point out possible risks or importance of certain factors. Sensitivity analysis will be used in this research to initially point out the most influential uncertainties and/or policies and to assess interaction effects between them. Saltelli (2010) particularly describes global sensitivity analysis (GSA) to evaluate the impact and interactions of uncertain inputs in complex models, by considering the output behaviour of the model over the full domain of uncertain inputs. Since GSA can be computationally heavy (especially when it is desired to additionally assess second order effects or higher), Jaxa-Rozen and Kwakkel (2018) suggest using variance-based Sobol indices as an effective alternative.

The Sobol technique uses variance decomposition to establish the contribution of each uncertain input to the unconditional output variance of the model, which can be non-linear and non-additive. The technique calculates three different "Sobol-indices" per parameter on a certain output (Jaxa-Rozen and Kwakkel, 2018; Sobol, 2001):

1. The first onder index $S1$: The main effect, representing the fraction by which the output variance would be reduced on average by fixing a certain parameter within its range.
2. The second order index $S2$: The fraction of output variance linked to a combination of 2 specific input parameters which is not captured by the superposition of each inputs first-order index, thus corresponding to interaction effects in a non-additive model.
3. The total effect ST: The total effect, including the contribution of the first-order effect and the sum of all higher-order interaction effects.

The difference $ST - S1$ indicates the importance of interaction effects. The $S1$ and ST will be used in the sensitivity analysis as a prior step to create a clear understanding on the importance of uncertainties and policies on the outcomes of the model, and to determine the importance of interaction effects. These indices are therefore used for factor prioritization, in which the input parameters with the highest main effects $S1$ would be assessed as most influential, and for factor fixing, where input parameters with $ST \approx 0$ can be judged non-influential and discarded from further analysis (Jaxa-Rozen and Kwakkel, 2018).

Additionally to factor prioritization and factor fixing, the Sobol-indices provide essential insights on the impacts of the input parameters on the model's outcomes. This means that when applying Sobol analysis on a model with specified policy levers, the importance of these policy measures are also highlighted. Because Sobol uses variance decomposition, in order for the indices to be interpreted correctly the model outcome distributions must be unimodal and symmetrical. When model outputs are not distributed symmetrically or unimodal results must be interpreted carefully or might not be meaningful.

2.4.2. Behaviour Based Scenario Discovery: Time Series Clustering

Scenario discovery reasons from a decision-making perspective: it looks for the inputs which generate subsets of outputs that are specifically relevant for decision-making (Lempert et al., 2008). This decision-making focus is highly relevant for the research at hand, for it is aimed at supporting the Ministry of Economic Affairs and Climate Policy in gaining insights on the effects of possible role demarcation policies on the development of an emerging market such as electric vehicle charging infrastructure.

Many different scenario discovery methods exist and to select an applicable method, one must look specifically at the problem at hand. This research aims at finding out how role demarcation policy influences the development of the electric vehicle charging infrastructure market. This means the research's performance metrics should be assessed not only on their end-state, but the behaviour over time should be considered. A rough example of the relevance of behaviour over time can be given by considering the Dutch housing market: Currently, average costs for a house are almost 20% higher than they were at the end of 2007. However, the prices actually dropped right after the financial crisis in 2008 and were lower than the initial (2007) value until mid 2017 (Wegwijs, 2018). The regression's shape over time is referred to as the behaviour of the metric and for relevant assessment of this development, a behaviour based approach should be taken. Steinmann (2018) proposes time series clustering for behaviour based scenario discovery. Instead of considering the influences of input parameters on a certain end-state, time series clustering analyses the outcomes by the shapes of their curves. When multiple time series are present, the ensemble can be separated into a number of clusters of similar behaviour based on specific similarity metrics. The influences of the input-parameters are then analysed to find out what factors mainly explain certain behaviour clusters. Because of behaviour-based character of time series clustering, the method is highly suitable for the combination with SD-models and to address development over time.

Following on Steinmann's research, time series clustering can be applied by the following approach (Steinmann, 2018):

1. Generate a large number of time series model outputs using a suitable sampling method. For sampling of an SD-model through EMA-media, Latin Hypercube Sampling will be used (Kwakkel, 2017).

2. Identify a suitable number of clusters in the data using a cluster validity index. Rousseeuw's (Rousseeuw, 1987) silhouette widths will be used, complemented by visual assessment to achieve desirable cluster counts.

3. Apply a suitable time series clustering algorithm to the data, partitioning the time series into a suitable number of clusters. Following on Steinmann's research, Complexity-Invariant Distance (CID) (Batista et al., 2011), Combined Temporal Correlation and Raw Values (CORT) (Chouakria and Nagabhushan, 2007), and Discrete Wavelet Transform (DWT) (Zhang et al., 2006) are used. From all 3 methods, the alternative is chosen which is concluded to result in the most useful partitioning, based on visual comparison. For this assessment, again visual inspection is required to determine the most desirable clustered partitions

4. For each cluster, induce the generative rule using a suitable method on the assigned clusters for each input-output paring as condition. The results will be visualised using a series of representations combined in a single pairs-plot, more specifically aimed at plotting the interactions between the parameters.

The identification of a suitable number of clusters is done by calculating and comparing validity indices of different cluster counts with preferably various clustering algorithms. Rousseeuw (Rousseeuw, 1987) compares the similarity of a certain cluster's members to each other compared to the similarity of the members with those of another cluster, giving the silhouette width of a cluster. The average value across all time series tends towards a value of 1 for perfect clustering solutions, and -1 for perfectly wrong solutions. The maximization of the silhouette width is therefore the first criterion for finding decisive clustering solutions. However, since the "perfect" or the statistically most valid number of clusters might not provide all the information the modeller desires, e.g. too many clusters can complicate understandability to undesirable extent, and too little clusters can exclude possibilities to draw conclusions from the data. Therefore, the silhouette width criterion is accompanied by a brief visual comparison. Similarly, different clustering algorithms are applied and the most suitable partitioning for assessing the problem at hand is chosen by visual inspection.

To induce generative rules from the clustered time series, 2-dimensional spaces of the inputs are constructed with a certain output as value. In this case, the values will be categorized by their membership to a certain cluster. This means that for each output clusters will be generated and the relevant input parameters will be plotted as input × input pairs, showing points coloured per cluster membership. This enables the possibilities to consider the influences of certain inputs on cluster memberships and their second-order interactions with other input parameters. By doing this across all parameters, the multidimensional influences of input parameters can be analysed.

2.4.3. Analysis phases

To complement and to summarize the past presented methods, the policy analysis steps can be presented stepwise. After conceptualisation of the system and model formalization, the identified scenarios and policies will be analysed. These analyses are separated into three different parts:

1. Base case analysis: The base case is the situation without any policy implemented. The outcome space will be analysed extensively by means of variance based sobol indices combined with time series clustering.
2. Defined policy analysis and comparison: All identified policy options will be independently tested on the model. The complete set of outcomes of all independently applied policies will together be analysed through time series clustering.
3. Mixed policies analysis: Combined policies and their interactions will be analysed by means of variance based sobol indices combined with time series clustering.

Since the defined policies are similar to the mixed policies but implemented differently, phases 2 and 3 will be done in parallel for comparative reasons. Each of the previously presented parts are performed in three different steps, concluded from former subsections but with a prior exploratory phase added:

1. Exploration: visual assessment of complete outcome space, prior assessment of performance metrics behaviour over time and validation of outcome scenarios and behaviour.
2. Sobol: factor prioritisation, factor fixing, and prior conclusions.
3. Time series clustering: assessment of impacts of uncertainties and policy options on desired outcome behaviour.

2.5. Research framework

The final research framework as designed by means of the previous sections can be summarized as followed: The research framework represents the order of the research. Note that the model analysis and policy analysis steps are not performed parallel to each other, but are represented as such to highlight the similarity of these steps. Base case (no policy) analysis will be done first, and during policy analysis and the discussion, the model analysis outcomes will be used for comparison.

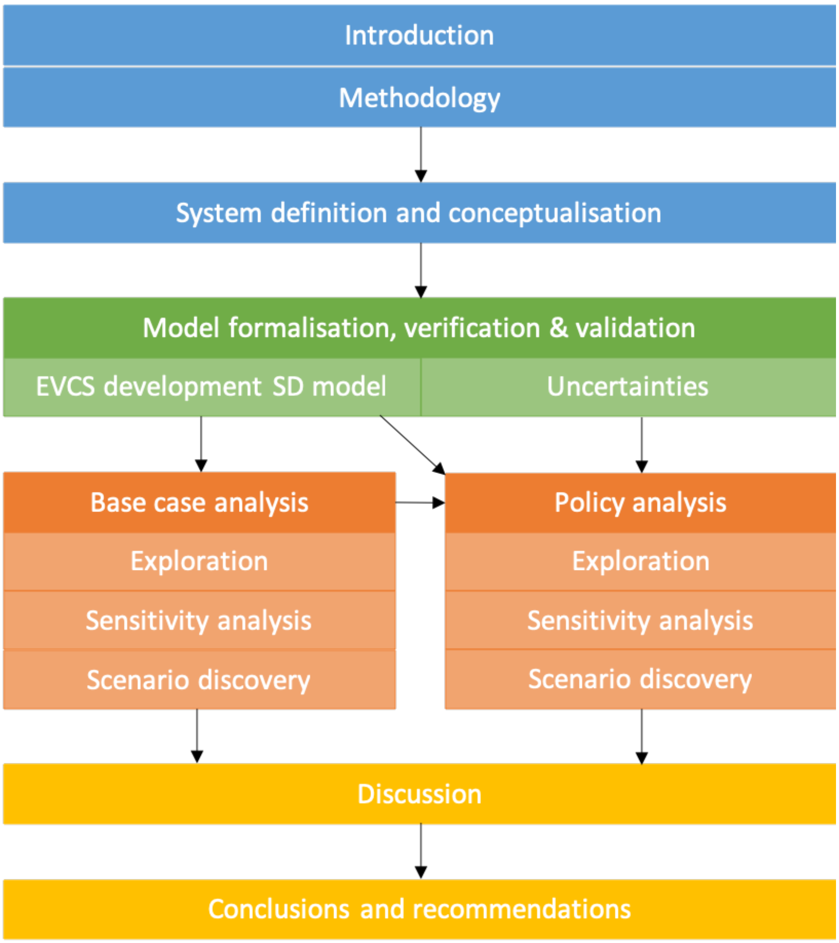


Figure 2.2: Research flow diagram. The colours indicate the dominant methods that are used for each part: blue is literature review and expert consultation, green indicates System Dynamics, orange indicates exploratory modelling and analysis, and yellow means the research itself is used as a main reference.

3 The EVCS development system

This chapter will describe the EVCS development system in qualitative terms. With the research goals and boundaries in mind, relevant concepts will be explored by means of literature research and expert interviews and consultations. Expert consultations were done by various meetings, e-mail correspondence, company visits and seminars and were all initiated in the name of the Ministry of Economic Affairs and Climate Policy. A complete list of experts consulted with corresponding expertise and organisation can be found in Appendix A. The following sections will assess the notion of market development, the relevant aspects of the EV charging infrastructure supply and demand dynamics, and what are the possible meaningful differences in investment behaviour between a network company and a common commercial party. Additionally, first estimations will be made concerning uncertainties or external influences on the system and possible policy interventions will be examined.

3.1. Market development

It is important to properly define the notion of market development within the research's context. For the Dutch Ministry of EA&CP, optimal market development is the ultimate goal. However, this is a very complex subject and without elaboration quite vague. In accordance with the Ministry, market development in this research is "the performance of a market over time in terms of price development, entrance barriers, and demand satisfaction" (Interview Ministry of EA&CP: Appendix A). Although seemingly straightforward, this definition of market development raises a number of dilemmas. In the following sections, these 3 parts of market development will be elaborated and their dynamics within the context of EV charging infrastructure will be discussed.

3.1.1. Price development

Price development as a measure is a relatively simple idea: the average price for EV charging infrastructure over time. To fully understand what price development implies in the EV charging infrastructure system, the EVCS business model should first be elaborated. Since energy infrastructure is unbundled by law from production, delivery and trade, the business case for a market party per single EVCS is the straightforward concept of covering the costs of the project by charging an additional charging fee as a mark-up per kWh added to the electricity price. The business cycle consists of the following phases in the (Schroeder and Traber, 2012; Serradilla et al., 2017):

1. Realisation: The planning, purchasing, building and installation of the charging station.
2. Exploitation: When active, the EVCS can be used by EV drivers who will be charged for the service.
3. Decommissioning: After a certain lifetime of the product, the EVCS will be decommissioned or replaced.

The realisation phase covers almost all capital expenses from material to installation costs. The decommissioning phase will in many cases also involve decommissioning costs, but in comparison to the costs for realisation this is can be neglected. This means that during the exploitation phase, all costs for realisation, decommissioning and operational costs during the exploitation phase itself should be covered for the project to become a feasible investment for market parties. The charging fee must therefore cover all costs during the lifetime of the product (Schroeder and Traber, 2012; Serradilla et al., 2017).

A significant proportion of the marginal cost of an EVCS comes from the production (Serradilla et al., 2017). The production cost of a product are subjective to improvement: through economies of scale or learning, production costs are expected to decline when scaling up or by experience through cumulative production (Künneke and Fens, 2007; Pruyt, 2013; Yelle, 1979). A market party can therefore individually gain advantage by being an early innovator and gaining experience, or by scaling up and more efficient production methods. The market price for public charging is a result of all marginal costs so by lowering marginal costs below the market price, profits will be maximized. These dynamics then create positive feedback loops through the price development on a market party's individual level, for higher profits means the investment will become more attractive, which leads to a higher investment rate, which can lower the costs through learning or economies of scale and increases profits again. Other costs like operational or installation management costs are more difficult to be lowered and their impact on the total costs is very low (Schroeder and Traber, 2012), therefore these values are assumed to be constant.

Since the charging fee applied per kWh, income is the product of the usage and the value of the charging fee. So to determine the marginal charging fee, the demand must be estimated first: higher use rates per EVCS results in lower marginal charging fees. Since the EVCS is an infrastructure, or facilitating market, the product's demand itself is almost entirely dependent of another (Künneke and Finger, 2009). In this case, this other product is the EV, which is driven by external developments. EV travel behaviour studies suggest however that from the entire population of potential EV owners, a certain ratio will always be in need of public charging infrastructure (Christensen et al., 2010; Kang and Recker, 2009; Weiller, 2011). Since this ratio of EV charging traffic will go through public EVCS, the market wide average cost of usage for an EV will proportionally depend on the EVCS price as well. This results in a positive feedback loop where higher demand means lower public EVCS marginal charging fees, which means lower cost of usage for an EV, which means a higher EVCS demand.

The final charging fees will additionally depend on the investment structure of a company. A company may strive for higher profits, requiring higher charging fees, or a competitive market may lower the profit goals of the market parties. Additionally, the nature of the capital of a company and risk estimations determine the interest rates that are added to an investment (Arnott and Bernstein, 2002; Eijgenraam et al., 2002). Investment behaviour of market parties thereby influence price development and is difficult to predict. The impacts of differences in investment behaviour can however be measured by monitoring price development under various assumptions.

3.1.2. Entrance barriers

Barriers to entry in a market are, together with profit expectations and stability, the key factor that companies consider in a new investment decision. Porter (1980) has identified the 6 most important entry barriers that dominate new market entry decisions: cost advantages of incumbents, product differentiation of incumbents, capital requirements, customer switching costs, access to distribution channels, and government policy. Karakaya & Stahl (1989) Have quantitatively tested the importance of these 6 barriers of entry on a generic market model. Their study concludes that the cost advantages of incumbents is most critical for all market entry decisions, which is consistent with Porter's theory about business-level strategy of cost leadership. Capital requirements and product differentiation follow as second and third most decisive barriers, where the remainders vary between different markets and deliver considerably less impact compared to the dominant 3 identified barriers.

Cost advantages of incumbents contains the advantages of incumbents through both economies of scale and advantages independent of scale like experience (Karakaya and Stahl, 1989). In infrastructure markets like the EVCS market, economies of scale is an important and expected process during market development. Experience is a very general notion that is assumed to be possible in any market, (Porter, 1980) therefore it is also logically expected to be present for different parties individually during the development of the EVCS market. Cost advantages of incumbents form a strong barrier that increases on the long-term: by scaling up production and increasing cost efficiency of production through experience lower marginal costs are created for incumbents compared to entrants. This means that the stronger these processes are, the faster incumbents create uneven competition towards entrants and the further the market develops, the higher these entrance barriers become. In the EVCS market this is an important process because this implies that there is a trade-off between cost efficiencies of market parties and the possibilities for market entrance. This implicitly suggests that there is a risk that when a NWC is active in the introduction and growth phases of a market, it may create a significant cost advantage over new market entrants which can result in undesired market dominance of a NWC on the long term. On the other hand, because of the market characteristics, it may be desirable for a NWC to enter and exploit the market on a long term because it can result in better market performance. Cost effectiveness is therefore an important measure of market development and should be considered through comparing cost advantages and resulting price developments over various scenarios.

Capital requirements as a market entrance barrier means that entrants are less likely to enter a market when there are needs to invest larger financial resources in order to compete or enter the market (Karakaya and Stahl, 1989). Building and exploiting an EVCS is relatively capital intensive, for the production costs are high and creating production facilities are even higher (Schroeder and Traber, 2012). This means that under general assumptions, a NWC could be more keen to invest on such a market because it has access to sufficient financial capital and is naturally experienced in operating on such markets. However, because production and exploitation/operation of EVCS is not necessarily done by a single organisation, the producers itself can increase cost efficiency through economies of scale and experience, lowering purchasing prices for operators and thereby lowering capital requirements as market entrance barrier. Now a hypothesis emerges: early activity by a NWC stimulate the initial development of the market, where market concentrations later would increase by lower capital requirements. This hypothesis will be tested through analysing cost development of the market, highlighting the capital requirements of the market.

Product differentiation of incumbents is a result of brand identifications or customer loyalties due to advertising by established firms. For a homogeneous product like electricity, little product differentiation can be initiated for it only delivers electricity. This research is directed to a national scale on a market wide level, meaning individual service differentiation like charging speed is only assessed as a market average. Additionally, product differentiation effects are regarded to be inconsistent for fast charging (no valid statements can be made based on rational indicators) (Sun et al., 2016), and consumer choices for electricity as a product are dominated by cost incentives (Woo et al., 2014).

Costumer switching costs and access to distribution channels are assumed to be absent. EV charging payment is typically done per kWh of usage exclusively and therefore switching costs are not expected (Schroeder and Traber, 2012). Competition is assumed to be entirely cost-based. Access to distribution channels is also a non-likely barrier, for the product is a distribution channel itself and limiting access to the service diminishes the value of the business model. Government policy affecting the entrance barriers however is included and an important focus, since the main goal of this research is to review impacts of certain policy options that are explicitly aimed at raising entrance barriers for NWC's hoping to result in lowering entrance barriers for commercial parties.

3.1.3. Demand satisfaction

The consumer side of market development concerns market diffusion of the product. In the case of infrastructure markets, an important distinction is present: the product itself is not an independent product, but it facilitates another. As a consequence the infrastructure market only emerges because there is an existing, relatively developed product in need for infrastructure facilities. An infrastructure market can therefore be seen as a facilitating market, and the product itself is completely dependent of another (Künneke and Finger, 2009). However, since there is already a developing and relatively predictable market for the product that is in actual need for additional services in the form of infrastructure, this also creates a great advantage. Compared to independent products, a facilitating product's success is guaranteed by the development of the subjected market, while also being able to stimulate the subjected market in return. In the case of EV charging infrastructure the electric vehicle market is the subjected market, driving the demand side of the charging infrastructure market. The consumers are EV drivers which initially based their choice of purchasing an EV instead of another type of vehicle on the specifications and attributes of the EV as a product itself, not on the specifics of EV charging infrastructure. However, the diffusion of EV's can be stimulated through development of the infrastructure market because of its facilitating nature (Hackbarth and Madlener, 2013; Jensen et al., 2013; Künneke and Finger, 2009; Van den Brink and Annema, 2007). Conclusively, the demand side of the EV charging infrastructure market is strongly driven by the external development of the EV market, but can be influenced interdependently by the charging infrastructure market. This statement means that while being relevant to monitor the demand for EV charging infrastructure to assess the influences of the market development, this can only be measured when constantly compared to the EV market as well. When EV owners increase, the demand for EV infrastructure increases with it proportionally. An important measure for market diffusion is therefore the EV infrastructure supply relative to the EV market and not the absolute demand.

Additionally to demand satisfaction in terms of actual supply and demand balance, the attractiveness of EV's is a relevant performance indicator. Since it is a facilitating market, its success can also be measured by investigating the impacts the development of the product has on EV sales. When EV sales in certain scenarios increase faster than in others, this means that the market for EVCS will grow faster in those scenarios and therefore the market will develop faster as well.

3.1.4. Market development conclusions

From the previous chapters it can be concluded that the EVCS market consists of 2 different layers: the physical product layer that represents the actual supply and demand numbers, and the investment behaviour layer that represents the decision-making process of market parties to decide if and to what extent investments will be made. The EVCS market development is the result of the interactions between these layers.

The outcomes of interest are derived from the three selected core concepts of market development: price development, entrance barriers, and demand satisfaction. Price development will be measured through the EVCS price per kWh over time. Entrance barriers that are identified as potentially critical are cost advantages and capital requirements, which are measured by the capital expenditures of market parties. Finally, demand satisfaction is concluded to be relative to the amount of EV's in the traffic mix and the possible positive effects to the demand side can be measured through EV sales.

3.2. Investment behaviour

As shown in the previous section, the investment behaviour of market parties influences many of the system dynamics. This section will explore the different aspects of investment behaviour on the EVCS market and the possible differences in investment behaviour between a NWC and a commercial party.

3.2.1. Investment dynamics of the EVCS market

The EVCS business model is driven by profitability of building an EVCS. This depends on capital expenditures, operational expenditures, expected demand, and the market price. The capital expenditures have generally been covered in section 3.1 and it can be concluded that from all cost categories, the purchasing or production costs are dynamic, due to economies of scale and experience. This affects the investment behaviour of market parties because it influences the final profitability of an investment: incumbents with lower costs are more likely to invest in new projects due to a higher profitability. This has a strong negative effect on the investment behaviour of entrants or less dominant incumbents: lower costs for incumbents create a lower market price, lowering investment attractiveness for smaller parties. The market price of EVCS is the average price added to the electricity price per kWh on the entire market. The final market price is the result of the proportionally combined prices set by each market party individually. Operational expenditures are assumed to be constant and therefore have a static and consistent impact on all market parties (section 3.1).

Expected demand influences investment behaviour by increasing the projected use rate of an EVCS. The investor is expected to monitor the market and predict future incomes by comparing the number of EV's with the number of EVCS on the market. At low supply rates, the use rate per EVCS will be higher and because a charging fee is paid per kWh the income per EVCS will be higher. Investment rates will therefore be higher at low supply rates and lower when there is high supply. This mechanism trades off with demand satisfaction because when demand is not satisfied the investment will be more attractive.

On local levels, competition applies on potential "hot spots". Spots with high convenience for EV owners like reserved sites within parking garages can be issued to the company who presents the best business model. However, due to the long expected term of development for EV's itself, on a national scale the areas of interest are considerably scattered, resulting in a relatively even distribution of the market (Namdeo et al., 2014). Direct competition is therefore assumed to be absent when in the development phase electric vehicles. This increases the importance of investment behaviour, because this means that market concentration is driven by investment rates of market parties. The differences in investment behaviour between a NWC and a commercial party can therefore shape each other's business model through the course of time.

Subtracted proportionally from final revenues are however the interest rates correspondent to an investment. The interest rate is a complex figure that is the result of both financial calculations and qualitative aspects. Mainly qualitative aspects differ per market party and therefore interest rates can vary significantly (Arnott and Bernstein, 2002). The interest rate affects the final profitability and thereby also the minimum price that an investor can maintain. This means that qualitative behavioural differences can also impact the investment behaviour of a market party significantly, which makes market party behaviour very uncertain. The qualitative aspects of interest rates concern risk perceptions that are captured in risk premiums. A risk premium is the return in excess of the risk-free rate of return that an investment is expected to yield and captures a compensation for investors who tolerate a certain risk (Eijgenraam et al., 2002). This means that when a certain risk is perceived, the risk premium represents this risk estimation by means of an additional demand of returns. The risk-free rate of return is the theoretical rate of return on an investment with zero risk, which represents the minimum return an investor expects for any investment. In practice, because of the unlikely event of an investment actually being risk-free, a risk-free rate is determined by equalling it to national treasury bond rates of return. In the Netherlands, a standard risk-free rate of 4% is advised by the Ministry of Finance (Eijgenraam et al., 2002). Since actual values can be anything but the relevance for this research is captured in differences between market parties, the combination of risk-free rates and risk premiums are defined as a single risk premium and the value for a commercial party is assumed to be a stable 4%.

3.2.2. Network Company investment behaviour differences

The vast majority of profits of a NWC originates from the DSO in the group, which means overall safe profits for the NWC. Added to the operational scale of the DSO's and the capital intensity of their activities implies substantial market power. In economic perspective this means that the NWC as a whole has the opportunity to take greater risks than common market parties, because they have more capital to spend and because the financial performance of a NWC suffers relatively less from a failed project (Burnham et al., 2017; Jamasb and Pollitt, 2005; Künneke and Fens, 2007; VEMW, 2017). Moreover, the 3 largest NWC's in the Netherlands whose DSO's together own around 90% of the entire Dutch electricity network (with the exception of the High-Voltage network owned completely by TenneT), Stedin Group, Alliander, and Enexis Group, all present their results by publishing consolidated financial statements (Alliander, 2018b; Enexis, 2018; Holding, 2018). This may raise the concern if cross-subsidization taking place within NWC's. It is important to mention that this is illegal and has not been determined officially (Interviews Enexis, Alliander, ACM, and Ministry of EA&CP: Appendix A), but has been a serious concern in the past because of the way it appeared. However, since it has never been officially observed, related parties are convinced this is technically not the case and because the discussion was strictly political and already resulted in intensified monitoring it is assumed that this indeed was not and still is not the case (Kleijne, 2016). The effects of the consolidated financial statements and the minor impacts of the financial results of a subsidiary company are then limited to the inability of sufficiently assessing the exact effects of these subsidiary companies on final results and dividend payments. In practice this specifically results in the ability to undertake economic activities under higher financial risks, made possible by the negligible impacts and the insufficiently clear effects of these activities (Kogan et al., 2009).

The low impacts affect another interesting area: shareholder supervision. Shareholders influence a company's policy from a financial perspective: their benefits lie with dividend payments, and they thereby generally stimulate profit maximization of a firm (Jensen, 2010). Since the shareholders in this case are public parties and public interest is also embedded in the NWC's policy requirements, NWC's regularly find more incentive to invest in less profitable activities for public reasons (Jensen, 2010; Künneke and Fens, 2007; Van der Wal et al., 2008). Public oriented investments under higher investment risks are therefore, encouraged, and allowed because of public interest and the negligible impacts of failed experiments. In addition, the dividend payments easily remain sufficiently positive, providing little incentive for stakeholders to monitor or assess investment risks. Additionally, risk premiums are demanded less opportunistically in public project because of the public values involved and because of the investor's public function (Klein, 1997).

The main investment behaviour differences are therefore found in financial capital and risk calculations. The financial capital of a NWC is substantial and a regular market party is assumed to have less, to provide less, or have and provide at most an equal amount to operate on the same market. The differences in financial capital influence the investment rates of market parties: a higher capital allows a higher maximum investment rate because it is less likely to reach its spending limit. The risk calculations however indirectly affect the investment rates by influencing return on investments. The NWC is expected to calculate either lower or similar risk premiums compared to a commercial party. The differences in financial capital and risk calculations are the main drivers of investment behaviour.

3.2.3. Investment behaviour conclusions

Investment behaviour drives the differences between market parties and determines market power on the long term. Market power of a company on the long term depends on the investment rates compared to other and these differences are uncertain. Access to financial capital and public interest provide the basis of the possible differences in investment behaviour between a NWC and a commercial party: the main drivers of a difference in behaviour are financial capital and risk calculations. Additionally, the investment rates are based on investment return predictions, which will be used as an important metric of interest.

3.3. Outcomes of interest

Throughout the previous sections the most important outcomes of interest are identified. Although not yet in measurable formats, the following key performance indicators have been identified:

- EVCS charging fees
- Capital expenditure differences
- EV infrastructure supply relative to the EV market
- EV sales
- Return on investment (ROI)
- Market shares of different market parties

3.4. Uncertainties

During the system considerations, some key sources for uncertainty have been identified. First, the demand side of the market is considerably uncertain: the EVCS market's demand is a product of the vehicle market. The development of the vehicle market is mainly external, however some stimulant can be provided by developing the EVCS infrastructure facilities. The uncertainties lie within the completely independent external part of the vehicle market development. Another important uncertain aspect of the system comes from economies of scale or learning curves: it is very difficult to determine in an emerging market to what extent learning effects or scaling benefits are present. For being able to design policy for such a system it is very important to have a clear view about the benefits of economies of scale in order to be able to judge whether these effects are significant, which makes decision-making increasingly complex when targeted at undeveloped markets. The goal of this research is to contribute to the ability to develop policies for emerging markets and therefore the uncertainties related to learning effects and economies of scale are considered to be an important aspect of the system. The final category of uncertainties is the investment behaviour differences. As stated in Section 3.2 and similar to the learning and economies of scale effects, literature study shows the probability of a NWC showing different investment behaviour based on its characteristics. Although it is clear that a NWC would invest more when profitability is high due to its probable higher access to financial capital, because a NWC can realise returns easier because of lower financial risk valuations, or because a NWC would accept lower profits because of public interest, it is impossible to make actual assumptions regarding the extent of these behavioural differences. Investment acceleration, risk valuation, and profit target differences are therefore considered to be uncertainties. Conclusively, the following uncertainties have been identified:

- Vehicle market development
- Economies of scale parameters
- Learning curve parameters
- Investment acceleration differences
- Risk valuation differences
- Profit target differences

3.5. Policy options

Role demarcation policies can roughly be categorized into 2 main categories: restriction or activity boundaries. Restriction is the complete restriction of a market party to participate on the market, in this case meaning that one of the policy options is simply forbidding any activity by a NWC on the EVCS market completely. Activity boundaries are a mild form of restrictions in the form of setting a certain threshold on a market aspect. For instance in the electricity market, the network companies are unbundled from any vertical integration (Wijers, 1997). EV charging infrastructure however eventually falls under the term of energy infrastructure, already demarcating the possibility to sell or produce electricity through the same law (ACM, 2016). Moreover, demarcating different segments of the market is focused on the entire market and all market parties participating on it, where this research is focused specifically on the impacts of a NWC on such a market and how demarcation policies aimed at NWC's affect that development. Therefore, the remaining activity boundary measures are mainly focused on applying the proposed "temporary activity" (ACM, 2017c), or setting a boundary on the market share of a NWC. The temporary activity is an initiative based on the urge of NWC's to stimulate developing markets by taking prior initiative on that market: when a market does not develop sufficiently in the eyes of the regulator, a NWC can be allowed to enter the market for a limited period. This is a very new initiative and its effects are not yet observed or considerably estimated, making it a very suitable policy option to include in this research. The market share cap is even more conceptual and will be included as a candidate policy implementation as well.

s and because individually they own just a portion of the NWC, history learns that this public group of shareholders does not act as active as a typical commercial shareholder when it comes to financial control (Interviews Ministry of EA&CP and Ministry of Finance: Appendix A).

For a complete view of the policy scope, "no policy" is included as an alternative and a reference. Conclusively, the following role demarcation policies will be analysed in this research:

- No policy
- Full market entry restriction
- Temporary market entrance
- Market share cap
- Shareholder activation

3.6. Conceptual model

To conclude the outcomes of the conceptualisation of the system, the conceptual system can be visualised using the XLRM structure by Lempert (Lempert et al., 2003) in figure 3.1.

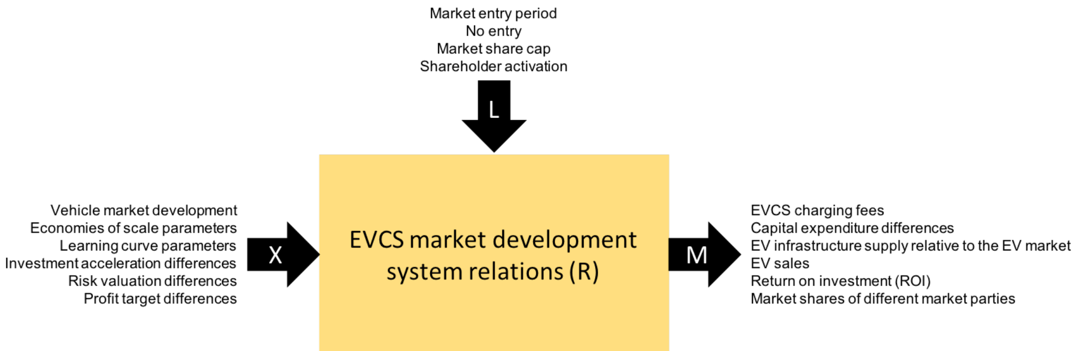


Figure 3.1: The conceptual model shown in XLRM representation.

The uncertainties, policy levers and metrics of interest have been identified, and the concepts of the system relations have been explored. The system relations will further be defined in the next chapter, based on market development relations and investment behaviour dynamics as presented in the previous sections.

4
Model design

This chapter explains the model formalisation of the SD model that simulates the development of the EVCS market, within the research goals and system boundaries. The following sections discuss the main structures of the model and explains the chosen modelling decisions. A detailed overview of the model, parameter values, constants, and uncertainty ranges with their corresponding literature references can be found in Appendix B. Three main structures have been defined: EVCS supply structure, vehicle development structure, and the EVCS returns structure. The model is built in Vensim (DSS, version 7.2a Single Precision) and the main structures have been separated in different views.

4.1. General model structure

Market development itself has been explored variously by applying System Dynamics. As with all unique situations, a perfectly fitting archetype for modelling the EV charging infrastructure market development is not readily available. However, the strength of using System Dynamics as a method lies with the range of fundamental structures that can be used for modelling basic dynamics and when combining a multitude of these structures, a realistic interaction between different dynamics can be modelled (Forrester, 1994). For this research, the foundation of the model is found by starting with a supply-price-demand feedback structure by Sterman (2000) as presented by a Causal Loop Diagram (CLD) in Figure 4.1.

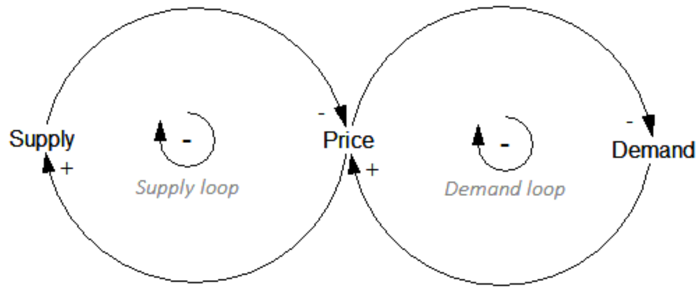


Figure 4.1: CLD representation of the supply price demand model by Sterman (2000). Arrows indicate a causal influence and the sign indicates the direction of the influence. The circular arrows with a sign in the middle represent feedback loops and the sign indicates whether the loop is positive or negative.

The model connects the supply and the demand by defining feedback effects with the price of a certain product or service. Typically, market dynamics are characterised by this structure where the price is a variable that interacts with both supply and demand, where supply and demand are shaped by sector- or market-specific dynamics. To find these specifics the modeller should follow qualitative research methods and translate relevant theories into the model. This bottom-up approach is used in this research as well and will be presented throughout the following sections. First, a high-level view of the system is presented, followed by increasing the model resolution by studying all different identified structures individually.

The findings from Chapter 3 have pointed out the essential aspects of the EVCS development system: vehicle development, EVCS supply processes, and investment behaviour. Since the investment behaviour is eventually a result of a synthesis of the demand development, the supply rates, and the projected returns on the market, the model is divided into three main structures: the EVCS supply structure, the vehicle development structure, and the EVCS returns structure. The vehicle development influences the demand for EVCS. The EVCS supply structure includes the actual investment on the EVCS market by different market parties and the resulting realisation of EV charging infrastructure, which is generally captured by the supply loop in the basis structure shown in Figure 4.1. The EVCS returns structure determines profitability, the EVCS market price, investment risks, and cost development of EVCS. A high level causal loop diagram of the model is shown in figure 4.2.

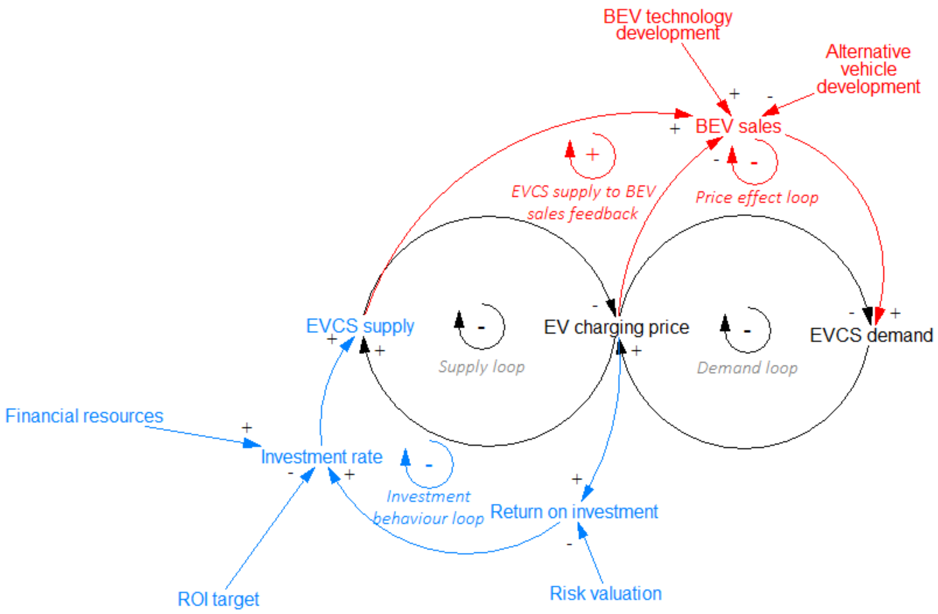


Figure 4.2: High level CLD of top down model. Arrows indicate a causal influence and the sign indicates the direction of the influence. The circular arrows with a sign in the middle represent feedback loops and the sign indicates whether the loop is positive or negative. Indicated in blue are parallel market party processes, and highlighted in red are vehicle development processes..

The model processes that describe market party decisions and behaviour are subscripted in the model: the processes run in parallel for every market party separated. These processes are indicated in blue in the figure. The vehicle development process influencing demand is presented in red. The centre structure represents the fundamental market dynamics and the supply structure. The main goal of the research is to investigate the impacts of the presence of a network company on a market. Chapter 3 illustrated that the essence of this problem is the difference in behaviour between the two market party types. Thus, since the fundamental aspect of the problem considers the differences in market behaviour of the average commercial party and the average network company, the system will be modelled as a duopoly, separating both party types in two classes: commercial and NWC. The parallel process therefore represents a parallel process of both the commercial parties acting on the market and the NWC's.

As for modelling conditions, the simulations are measured and defined on a yearly scale, with a total time period of 20 years. The time period is based on the development speed of the problem up until now (mainly based on discussions: a lot has happened until now and the discussion seems relatively settled down), combined with the lifetime of the product of little over 10 years. A period of two lifetimes of an average EVCS is taken. Additionally, the market is simulated from 2010 until 2030. The starting time of 2010 has been chosen because it is the furthest back in time where relevant data can be found and it allows the possibility to validate the model outcomes partially.

4.2. EVCS supply structure

The EVCS supply structure is created by following a SD supply cycle which divides the supply chain into 3 phases: proposal, realisation, and decommissioning. The original structure by Sterman (2000) models a production process, however the standard 3 steps structure basis used here is inspired by the modification by Auping (2016) which adjusts the structure to fit utility sectors. In between the phases, 2 stock values are measured at every time step: number of EVCS in preparation and number of Active EVCS. The proposal is influenced by investment rates, which are determined by processing inputs from the other model structures (sections 4.3 and 4.4). Generally, the EVCS supply structure can be divided into 2 parts: Project initiation and project operation. The following section will explain both processes. An overview of the SD model of the EVCS supply structure is shown in Appendix B.1.1.

4.2.1. Project initiation

Project initiation starts with the investment decisions of market parties. Manufacturer and infrastructure provider investment decisions depend on their cash flow expectations which are captured in the Return on Investment (ROI) in the EVCS returns structure (section 4.4). A positive ROI means the project will be profitable, a negative ROI means it will suffer losses over the entire project's lifetime. The ROI differs for each market party class and the investment decisions will therefore be calculated separately as well. Sterman (2000) has pointed out ways to translate cash flow expectations into investment decisions. Assili & Ghazi (2008) have later suggested that an improved version by Olsina, Garces, and Haubrich (2006) is more suitable for modelling aggregated investment behaviour the general model by using a profitability index and an aggregated investment responsiveness which are used to estimate investment rates for a certain technology. This calculation has been used in the EVCS supply model to translate ROI values to a market party's investment rate.

Following the framework by Olsina et al. (2006), the profitability index is similar to the ROI, but its long term equilibrium value (costs equal income) lies at 1, instead of 0. As a result, the profitability index is a simple conversion of the ROI:

$$PI = ROI + 1 \tag{4.1}$$

To follow natural investment incentives, Olsina et al. (2006) has used a logistic function to describe the aggregated investment responsiveness to the profitability index:

$$AIR(PI) = \frac{AIR_{max}}{1 + e^{-(\lambda PI + \gamma)}} \tag{4.2}$$

Where AIR is is the aggregated investment responsiveness logistic function, AIR_{max} is the maximum value of the logistic function, and λ and γ are the parameters of the function. When the minimum value AIR_{min} is set at a constant value, the parameters can be computed as:

$$\lambda = ln\left(\frac{1}{AIR_{max} - 1}\right) - \gamma \tag{4.3}$$

$$\gamma = ln\left(\frac{AIR_{min}}{AIR_{max} - AIR_{min}}\right) \tag{4.4}$$

The minimum value is estimated at 0, representing no investment. The maximum investment rate should be estimated and partially depends on the willingness of a market party to increase investment rates as a response to increased profitability (Assili et al., 2008; Olsina et al., 2006). Because of the assumed difference in purchasing power and incentives between market party classes, different saturation levels (AIR_{min}) have been assumed for a commercial party and a NWC. To represent this possibility for a NWC to have a higher saturation level, a NWC public incentive investment boost has been added to the model, which adds a certain value to the AIR_{max} of the NWC compared to the standard saturation level of a commercial party which is set at 2 (double the amount of EVCS will be initiated compared to the prospected demand). Finally, the investment rate can be computed as:

$$\textit{Investment rate} = AIR(PI) \cdot \textit{Desired new EVCS} \tag{4.5}$$

Where

$$Desired\ new\ EVCS = (EVCS\ demand - \sum EVCS_{active}) \cdot \delta \tag{4.6}$$

Where δ is a delay time of 3 years for the construction of a new EVCS (Schroeder and Traber, 2012; Serradilla et al., 2017). New EVCS proposed is determined by applying the investment rates on the market-wide values of the desired new EVCS. Since the investment rates are meant to be an aggregated calculation, the values are also market-wide. However, because there are 2 different market party classes, the combined proposed EVCS will be twice as high. To maintain a proper supply and demand balance, a simple correction is made by divided each investment rate by the amount of market party classes in the model.

4.2.2. Project operation

From the moment that an EVCS is in preparation, it takes 3 years for an EVCS to be realised into an active EVCS . On the other side of active EVCS stock, the total amount decreases due to the lifetime of an EVCS of an average of 12 years, based on the estimated lifetime of 10-15 years (Schroeder and Traber, 2012; Serradilla et al., 2017). The total active EVCS per market party class is then determined by a constant inflow of EVCS realisation minus the decommissioning of EVCS after 12 years of operation.

4.3. Vehicle development structure

The function of the vehicle development structure in the model is to simulate the BEV market penetration in the vehicle market, with which the demand side is simulated. The research case is about public charging infrastructure and therefore the structure is based on the development of the passenger car market. The development originates from new car sales, which either add to the total traffic or replace former owned cars. The sales function determines the new vehicle sales distribution, which directly influences the distribution of all added cars to the system through an adjustment delay of 10 years, corresponding to the suggestions by van den Brink & Annema (2007). An overview of the SD model of the vehicle development structure is shown in Appendix B.1.2.

4.3.1. Vehicle classification

Similar to various research done by the International Energy Agency (IEA), 3 main vehicle types have been distinguished: Internal Combustion Engines (ICE), Plug-in Hybrid Electric Vehicles (PHEV), and Battery Electric Vehicles (BEV). This simplification is made because all of the essential variations between vehicle classes can be highlighted this way: all ICE classes run on conventional fossil fuels and are developed (their attributes are not expected to change significantly), and BEV is the dominant competition, which is still in the prime of its development and many research is available concerning possible development trajectories (IEA, 2017, 2018). The PHEV class is an exact combination of both of these classes, for it is a hybrid combination of both. A fourth class is added to represent any possible breakthrough technology as an alternative vehicle class: Other. This simplification is justified by a relevance statement: it does not matter what technology or what specific characteristics an alternative would consist of, the only relevant aspect is the possibility of radical development of any alternative vehicle class. By this reasoning, the model takes the possibility of the overall attractiveness of the 'Other' class radically increasing into account, which is not fragmented into different parameters. Additionally, it is assumed that an alternative vehicle technology will not penetrate the market when it is not a sustainable alternative (therefore by previous definition it is no ICE), and it will not be battery based but a significantly different source is assumed because otherwise it would be classified as a BEV (therefore it is no BEV or PHEV).

4.3.2. Traffic increase and replacement

The total traffic stock represents the actual amount of active passenger cars on the road at a certain moment in time. The total traffic is modelled as a balance: there is no research found that significantly expects the total traffic to decrease in any realistic future scenario (CBS, 2018a; Schubert et al., 2014), this means that it is not necessary to create a complex structure that may or may not increase or decrease the total traffic amounts by means of various detailed factors. Instead, it is necessary to simulate the expected increase in total traffic and the expected replacement rate of passenger vehicles. The total traffic structure does not have an additional outflow, but has a feedback rate that serves as the replacement effect and which does not add to the total amount, it only replaces a certain ratio of all vehicles through the sales distribution. By this rate, the outflow is determined by comparing the least attractive cars (lowest sales distributions) with the most attractive cars (highest sales distribution) and adjusts the outflow to the desired replacement rates. Additionally, total traffic can increase by independent new car sales which do not replace old cars but add to the total traffic by combining the sales distribution and the expected increase of cars. Both rates of new cars added and replacement factor are based on trends derived from historical data from the Dutch Central Bureau of Statistics (CBS) (CBS, 2018a,b).

4.3.3. Vehicle sales distribution

The vehicle sales distribution is a continuous choice process. A most commonly used model for simulating vehicle (or any product) sales is discrete choice modelling. The discrete choice model determines attributes and corresponding parameters which represent measurable characteristics of a vehicle class and their corresponding valuation by consumers. This way for example vehicle class range or the vehicle class' cost per kilometre can, in combination with the determined parameters, quantitatively influence total vehicle attractiveness per class (Al-Alawi and Bradley, 2013; de Dios OrtÃozar and Willumsen, 2011). However, since the used model is on a continuous scale, some attributes can be aggregated or neglected. When removing the components that are only relevant on individual and discrete levels, a discrete-continuous choice model remains which represents a utility function of aggregated vehicle attributes and the coefficients associated with it (Derakhshan et al., 2015; Spissu et al., 2009). Also known as a multinomial logit model, or a multinomial logistic regression. The utility function is defined as:

$$U_i = \sum_{j \in a} \beta_j X_{i,j} + \epsilon_i \tag{4.7}$$

$X_{i,j}$ is an explanatory variable for attribute j (measurable or observable, for example emissions or fuel costs) for alternative i, where a is a set that includes all attributes. β_j is the slope parameter for explanatory variable $X_{i,j}$, and ϵ_i is the alternative i random component, or error term, used to include unexplained variance in the model (Derakhshan et al., 2015; Spissu et al., 2009). The utility function is used to determine the vehicle sales distribution by comparing all alternative utility outcomes. Equation 4.2 shows how these utilities are compared and translated into a ratio per vehicle class:

$$S_i = \frac{U_i}{\sum_{i \in n} U_i} \tag{4.8}$$

Where

$$\sum_{i \in n} S_i = 1 \tag{4.9}$$

S_i is the sales distribution of alternative i, where n is a set of all potential alternatives. All sales distributions are ratios, therefore summarizing the complete set must be equal to 1. The error term in 5.1 is used as a static base value for each vehicle class' attractiveness. From a comparison of research by Jensen, Cherchi, and Mabit (2013), Van den Brink & Annema (2007), Hackberth & Madlener (2013), and Wansart & Schnieder (2010), the following consistent explanatory variables have been identified: retail price [€], emissions [ton CO2/km], charging speed [minutes/charging session], facilities [charging or fuel stations/(vehicle*desired CS per vehicle)], costs per km [€/km], and range [km]. The corresponding slope parameter values are also derived from different studies by averaging relevant parameter findings and adjusting the ensemble to a continuous setting by summarizing discrete elements into a proportional base attractiveness value (error term). The exact parameter numbers and their corresponding literature references can be found in Appendix B.2.

4.3.4. External vehicle attribute development

External vehicle attribute development is modelled by following technology development theory. Technology developments can be modelled variously, but the basic development curve is mathematically characterized as an s-curve (Tilindis and Kleiza, 2017). While many complex statistic regression techniques can be used, when predicting unknown developments and estimating possible development courses, a basic logistic function is sufficient when details are less relevant (Christensen, 1992). Since for the EVCS market development the aim is to explore various possible future outcomes rather than accurately predicting a single future outcome, a detailed representation of all technological developments is not necessary. Additionally, the Netherlands is not a dominant producer on the vehicle market, therefore the development of vehicle attributes is assumed to be solely influenced by external factors (Statista, 2018). Hence, for exploratory reasons, possible development trajectories in the vehicle development model have been modelled as a logistic function with the possibility to vary the maximum value, offset, and steepness of the curve. The logistic function is a common sigmoid curve (s-curve) that represents both technology improvements and cost reductions by increasing efficiency in production, which is defined as:

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}} \tag{4.10}$$

Where e is the natural logarithm base, also known as Euler's number. x_0 is the x-value of the curve's midpoint, L is the maximum value and k represents the steepness of the curve (Reed and Berkson, 1929). In the model these values will be used to represent the development of a technology: the maximum value represents saturation of technological improvements or increasing production efficiency, the steepness represents the speed of the development, and the curve's midpoint can be used to offset the moment of development.

BEV technology development has been monitored for a longer time already and historical data is available. Battery power and costs, and drive-train development are the main technical drivers that affect the parameters identified above, where more specifically retail price, costs per km, and range are affected (Wansart and Schnieder, 2010). These technical drivers are represented in the model by factors range, costs per km, and retail price. Other drivers for the vehicle class effectiveness like sustainability (emissions) and charging facilities are influenced differently: emissions is static (always 0, since a BEV itself does not emit any CO2), and charging facilities is an internal factor in the system.

ICE technology development is modelled relatively simple, for its development is assumed to be saturated and therefore attribute values are static. ICE technology is a matured technology, fuel stations are widely available and the market has long been matured as well and this is not expected to change in the nearby future, and the increasing desire for sustainable transport results in increased taxes while decreasing relative utility for ICE vehicles through the sustainability attribute. Technology and market maturities result in slow growth rates and the sustainability trends significantly balance out their positive effects, and therefore the attribute values are considered static (Chan, 2007; Wansart and Schnieder, 2010).

The 'Other' category is a combined uncertain category which represents the possibility of any alternative technology breakthrough. Possibly represented by technologies like Hydrogen fuelled cars, Fuel Cells, Formic Acid, or a yet unknown technology, it is unsure and because of the main goal of this research also irrelevant. What is relevant is that it might, however currently relatively unlikely, be possible that there may be a technological breakthrough somewhere in the future which may suddenly sky-rocket the development of an alternative vehicle class (Chan, 2007; IEA, 2017; Wansart and Schnieder, 2010). Narrowing down the definition of the "other" categories development means that the general development can be captured by directly simulating a development curve (the s-curve) on the utility, or attractiveness, of this class. A single sigmoid function is used as input for calculating the utility of the 'other' class, with a variable static maximum, steepness, and offset.

PHEV's are an exact combination of BEV and ICE technologies. Therefore, the attribute values can be modelled as a whole by combining the attribute values of BEV and ICE proportionally to the average ratio of either technologies in a PHEV drive-train. The effects of PHEV on the markets work similarly, for example the demand for charging facilities is influenced by PHEV's proportionally to the average ratio of BEV and ICE technology in a hybrid vehicle.

4.3.5. Internal vehicle attribute development

The attributes of the various vehicle classes are influenced by internal processes of the model as well. These attributes are the facilities factor and the charging speed factor. The charging speed factor represents the negative influence of charging or refuelling time per minute of the duration (Jensen et al., 2013; Van den Brink and Annema, 2007) and is influenced by the development of the EVCS market through learning curves (section 4.3.2.). The facilities factor is a direct comparison of the amount of active EVCS and the demand for EVCS. The demand for public EVCS depends on a ratio of the number of EV's in the traffic mix. Both travel behaviour research and EV activity based assessment suggest that the proportion of EV charging traffic through public facilities is relatively constant and lies between 20% and 30% (Christensen et al., 2010; Kang and Recker, 2009). As a contrast, electricity demand impact study suggests that it will increase from 24% at current BEV shares to 29% when everyone would own a BEV (Weiller, 2011). Since an increase of only 5% is extremely small relative to the increase of BEV share (from current rates below 5% to full market coverage of 100%), in this analysis here, a 25% rate will be used.

4.4. EVCS returns structure

The EVCS returns structure is aimed to simulate the estimation of prospective profits of the investor. By processing market data at a certain moment in time, the companies can determine the expected returns of a new project when initiated at that exact moment. The EVCS returns structure calculates expenses and estimates incomes through market prices and demand rates, and uses this information to estimate the future Return On Investment (ROI) of a new EVCS project. The EVCS returns structure can be divided into 5 parts: Operational Expenditures (OPEX), Capital Expenditures (CAPEX), EVCS demand, Return on Investment (ROI), and EVCS Market Price. The basic business model itself is relatively simple: a charging station is built and incomes are generated by a mark-up price per kWh transferred to the costumer. The detailed constructions on how returns are made and how expected returns are internally estimated however are elaborated in the following sections. An overview of the SD model of the EVCS returns structure is shown in Appendix B.1.3.

4.4.1. Operational Expenditures (OPEX)

The expenditures for a public charging infrastructure project are based on two different business model studies by Schroeder & Traber (2012) and Serradilla et al. (2017). The different cost categories are identified similarly to Serradilla and on general levels compared to numbers by Schroeder & Traber. For the OPEX, the first simplification is however made by excluding standard electricity costs from the model. The reason for this exclusion is the irrelevance of these costs: because of unbundling laws (Wijers, 1997), exploitation of an EVCS is only possible through service costs and cannot be related to electricity trade or production, therefore electricity prices are assumed to be compensated by the costumer at the exact retail price on that moment, at that location. The remaining OPEX cost categories are all static, accept for the maintenance costs:

- DSO annual costs: The annual costs that a DSO charges for the connection. Static value of €1000 per year, based on a cost calculation by Hop & Helleweerd (2013).
- Estimated back-office running costs: Company costs and software or server capacity costs combined. Static value of €400 per year (Serradilla et al., 2017).
- Maintenance costs: Yearly estimated maintenance costs. Based on a rule of thumb from both business model studies: 7% of the charging station purchase costs (Schroeder and Traber, 2012; Serradilla et al., 2017).

The final OPEX for a new EVCS is the sum of all above costs. The OPEX is dynamic due to the maintenance cost calculation and is used on each time step to calculate the OPEX for new EVCS.

4.4.2. Capital Expenditures (CAPEX)

The CAPEX of a public charging infrastructure project is, similar to the OPEX, based on the two different business model studies by Schroeder & Traber (2012) and Serradilla et al. (2017). Serradilla points out 5 different categories: New power connections, site preparation, site costs, installation project management and operation, and charger and delivery costs. Schroeder & Traber simplify this to material costs, grid reinforcement costs, and installation costs. For clarity, in this model the 5 categories by Serradilla have been used, while comparing combined values of these categories to the aggregated classifications and corresponding values by Schroeder & Traber. The CAPEX costs are defined as:

- New power connections: One-time costs for installing new power connections (including the possibility for installing new transformers) to facilitate the desired load for an EVCS. A static value of €10.000 is assumed (Hop and Welleweerd, 2013; Schroeder and Traber, 2012; Serradilla et al., 2017).
- Site preparation: The total costs for physically preparing the site. Static value of €10.000 is assumed (Serradilla et al., 2017).
- Site costs: The average costs for buying property sized to fit a standard parking area for a single vehicle of 2x2,5 meters. A static value of 450 is assumed (Huisprijskompas, 2018; Serradilla et al., 2017).

- Installation and project management costs: The costs of installing the EVCS up to the point that the station is active. A static value of 4500 is assumed (Serradilla et al., 2017).

- Charger production and delivery (or material costs): Initial costs are assumed at €45.000 per EVCS (Serradilla et al., 2017). However, this value can decrease due to the learning curve of a market party (Schroeder and Traber, 2012). The learning curves are based on the active EVCS per market party and will be elaborated below.

Cost reductions due to learning on the production side of a supply chain are a realistic process which is assumed to occur in any functioning market (Yelle, 1979). The learning curve is therefore applied here to the production or material costs of an EVCS. The learning curve can be described through the following formula:

$$C_t = C_{t-1}\left(\frac{X_t}{X_{t-1}}\right)^e \tag{4.11}$$

C_t represents the costs at time t, X_t is the cumulative historic amount of active EVCS (all ever installed EVCS up to point t), and e is the learning curve parameter (Pruyt, 2013; Yelle, 1979). Equation 4.5 returns a cost reduction when total production numbers increase. To additionally simulate possible market parties' benefits from economies of scale or individual adjusted knowledge, the learning curves are separately used for each market party. As a result, the different market party classes can outrun each other on the long-term. Since the market parties are modelled as a duopoly, it can be argued that the economies of scale effects are smaller with commercial parties than with the NWC's, since there are expected to be significantly more potentially entering commercial parties than NWC's. However, because of the increased competition when multiple parties are active and because commercial parties are more sensitive to competition-related incentives, the cost reducing learning curve is stimulated as well. Since on this level of aggregation it is impossible to simulate the development of or to make assumptions about the number of market parties or the sensitivity to competition of these market parties, the learning curve is assumed to be similar for both parties.

The increase in application of charging infrastructure is also expected to improve the products specifications (Schroeder and Traber, 2012; Serradilla et al., 2017). The single specification that is relevant in this model is the charging speed of a charging station. A learning curve has been applied to the entire market capacity that creates a positive feedback loop with charging speed: the more EVCS there are created on the entire market (all market parties' supplies combined), the more the fast charging technology develops and charge times decrease. This effect influences vehicle class utilities through the vehicle development structure.

The final CAPEX for a new EVCS is the sum of all mentioned costs, depending on the development of costs through the learning curve. The CAPEX is therefore dynamic due to learning curves and is used on each time step to calculate the CAPEX for new EVCS.

4.4.3. EVCS demand

The EVCS demand is based on the total amount of BEV's and PHEV's, adjusted by the previously established use rate of 25% (section 4.3.5). The demand is defined in terms of kWh per year. This means that the average EVCS demand represents the total amount of energy demanded through public charging per year. Based on a standard BEV efficiency of 15kWh/100 km and an average daily travel distance of 41km, the daily average demand per BEV is estimated at 6.15kWh (Schroeder and Traber, 2012). Multiplied by the amount of BEV's and a proportion of the amount of PHEV's gives us the daily demand at a certain point in time. Finally, this is multiplied by 365 to translate the demand to a yearly basis.

4.4.4. Return on Investment (ROI)

There are several different ways of indicating the expected returns or profitability of a project. In this analysis, the most practical outcome would be a value in the form of a ratio (0 would be break even, 0.5 would be a return of 50% on top of the invested capital). For this reason, the Return On Investment (ROI) has been used, from the business model analysis by Schroeder & Traber (2012). Since investment decisions are based on the net profit of an entire investment period, the ROI is calculated by determining cash flows by subtracting yearly estimated costs from yearly estimated incomes and projecting these cash flows over the entire investment period. The investment period is set at 10 years to correspond to the average lifetime of an EVCS. Annual net profit of the charging station operation is then compared to its levelised investment cost to calculate the Return on Investment (ROI) as a ratio:

$$ROI = \left(\frac{Annual\ net\ profit}{Levelised\ investment\ cost} - 1\right) \tag{4.12}$$

Note that the ROI here is not translated into a percentage by multiplying the outcome by 100 due to practical reasons for modelling the investment rates. As a rate, the ROI can be used more directly when measuring the attractiveness of an investment.

The annual net profit is calculated by multiplying the EVCS demand (section 4.4.3) with the current market price (section 4.4.5). The levelised investment cost (LIC) distributes total cost over over all years and takes an annuity factor into account, resulting in the negative side of the cash flow adjusted to interest rates or risk premiums:

$$LIC = \frac{cost}{year} = cost \cdot annuity\ factor \tag{4.13}$$

$$annuity\ factor = \frac{(1+i)^n + i}{(1+i)^n - 1} \tag{4.14}$$

With i being the interest and n being the lifetime of the project (investment period = 10 years).

The interest rate, also known as the internal rate of return, is based on either interest payments, inflation, obligated dividend payments and/or by risk internalisation. The interest rate is generally a combination of all mentioned, consolidated into a single figure that is meant to capture a projects projected risk (Alliander, 2018b; Enexis, 2018; Holding, 2018). These risks are based on market risk, or systematic risk, and by a risk premium that is typically demanded by shareholders who require a certain internal rate of return (Arnott and Bernstein, 2002; Jamasb and Pollitt, 2005; Klein, 1997). The systematic risk is the internalisation of the volatility of a certain market as a whole. However, infrastructure projects are typically non-volatile markets (Klein, 1997; Künneke and Fens, 2007), and since an exact risk calculation is irrelevant considering the research goal of this analysis, the systematic risk is neglected. The risk premium however may be different for different market parties, which makes it highly relevant to include possible variations in the model. Because at the end risk premiums are to a significant extent a product of shareholders' personal values and desires (Arnott and Bernstein, 2002; Klein, 1997), a risk premium is regularly estimated through national standards. The Dutch Ministries of Finance and Infrastructure and Water have provided guidelines for risk premium estimation for investment projects in the Netherlands and recommends a standard risk premium of 4% (Eijgenraam et al., 2002). The actually used risk premiums by the different countries are, for previously mentioned social, individual and 'human' reasons impossible to be accurately estimated, however possible effects of the characteristic differences between a NWC and a commercial party can be explored: the standard 4% risk premium is set as a static value for commercial parties, while NWC is assumed to be either equal or lower to the commercial parties' values (chapter 3). The risk premium of the NWC is therefore modelled to be a variable range between 0 and 4%.

4.4.5. EVCS Market Price

The EVCS market price is based on a combination of prices set by both market parties at various points in time. Proportionally to the market share of each party their prices are captured in an average market price. The dynamic structure of the market price is based on an energy price development structure by Auping et al. (2016) and adjusted to fit the EVCS model. This structure adjusts the price based on an aggregated level by processing new target prices by comparing them with current market prices through a delay. A delay of 3 years has been used in this model, which is by estimation the average age of all EVCS on the market at a steady exponential supply increase. The target price is calculated by combining market prices and market shares of each market party separately. Using the target price, the price is calculated by equation 4.15, where MP_t and TP_t are respectfully the market price and the target price at time t.

$$MP_t = MP_{t-1} + \frac{TP_t - MP_{t-1}}{3} \tag{4.15}$$

The basis for EVCS pricing for a new project for each market party is provided by a combination of the yearly expenditures of a project (OPEX & CAPEX per year within the EVCS lifetime) and the expected use rate of a charging station. The resulting costs per transferred kWh expected is the base price. A desired mark-up is added to capture additional costs for the project needed to result in a ROI of at 0 plus the desired ROI aim. The ROI aim is a mark-up added to the break even point of ROI = 0 to represent a desired positive return on investment. Because of the public values involved as a motivation for a NWC, and the mitigated desire for a NWC to strive for high returns (chapter 3), it is assumed to be a possibility for a NWC to set a lower ROI aim. An ROI aim ratio is therefore included which simulates the lower ROI aim of a NWC as a proportion of the ROI aim of a commercial party. The market prices for new EVCS per market party are reduced from the ROI calculation 4.12 and is defined as:

$$P_p = \frac{LIC_p \cdot (1 + ROIA_p)}{ED} \tag{4.16}$$

Where P_p, LIC_p, and $ROIA_p$ are the price, the levelised investment cost, and the ROI aim for market party p, and ED is the electricity demand per public EVCS in kWh. Following on equation 4.16, the target price is calculated by:

$$TP = \sum P_p \cdot MS_p \tag{4.17}$$

Where MS_p is the market share of market party p.

4.5. Outcomes of interest

The key performance indicators identified earlier in Chapter 3 can now quantitatively be implemented in the model. The six outcomes will be measured as followed:

- EVCS charging fees: The EVCS market price per kWh calculated via equation 4.15.
- Capital expenditure differences: The difference in CAPEX of NWC's or commercial parties, each calculated via equation 4.11, referred to as the CAPEX gap.
- EV infrastructure supply relative to the EV market: The ratio of active EVCS per BEV, calculated by taking the quotient of the total active EVCS and the total BEV in the vehicle mix.
- EV sales: The EV sales will be measured by monitoring the sales distribution of BEV, calculated via equation 4.9.
- Return on investment (ROI): The relevant ROI is that of a commercial party, since the goal is to let the market develop into an attractive market for commercial parties. The ROI of commercial parties is calculated via equation 4.12.
- Market shares of different market parties: The market share of NWC will be measured. Since the market is modelled with two market party classes, the market share of NWC implicitly measures the market share of commercial parties as well.

4.6. Uncertainties

The uncertainties in the model are identified in Chapter 3, and included in the structures in the previous sections. In order to implement the uncertainties in the model, the uncertainty ranges should be determined in order to limit the ranges to realistic boundaries. The following section will provide additional details concerning the determination of these uncertainty ranges. The uncertainties will be discussed by following the uncertainty categories as defined in Section 3.4.

The first category of uncertainties is the vehicle market development. The external effects in the vehicle development structure are the parameters of the development structures of still developing technologies. In terms of development, PHEV is a combination of two other technologies which is already processed within the vehicle attribute development structure, but the remaining 3 categories can be distinguished: ICE is considered to be fully developed, BEV is moderately developed, and the alternative "Other" category is undeveloped. For ICE, fuel prices have always remained an uncertain factor due to the global oil market (Auping et al., 2016). For this reason, the ICE fuel prices have been varied: the average fuel price in the Netherlands is currently

1.60 Euro including taxes (gasoline and diesel prices average, (brandstofprijzen.info, 2018)). Excluding taxes, a price of about 1,20 Euro remains, which is varied by 40 cents higher and lower, leaving a range of 0,80-1,60 Euro. The BEV development is sufficiently evolved, as explained in Section 4.3.4. However, the rate of the future development can not perfectly accurately be predicted. In the model, the projections by Wansart and Schnieder (2010) have been iteratively approximated by adjusting the S-curve parameters. The BEV development speed set at 0.15 resulted in reasonable similarity on both the costs and range developments, therefore this point is used as a reference with a lower and upper range of 0.5 added. The BEV development range is therefore estimated at a range of 0.1-0.2. The alternative vehicle technology development (the Other category) is very uncertain. The logistic function with the structure as described in 4.3.4 is therefore varied quite extensively: the total attractiveness of the alternative technology should be able to reach a maximum level that significantly influences the vehicle development structure. A value of 6 has been found to be a minimum value to result in significant influence within the period of 20 years. Setting a margin results in a range of 0 to 8 on the maximum possible attractiveness. The development speed has been referenced by the BEV development, but since many of the possible alternatives involve ICE-like drive-trains (hydrogen, fuel-cell) it is assumed to be able to develop even faster. Consecutively, it only seems reasonable to add a similar extra margin to the lower bound of the range, setting the margin at 0.05-0.35. The final uncertain part of the alternative vehicle development logistic function is the introduction year of the technology, of the offset of the logistic curve. Keeping in mind the start-up time of the curve (no increase in the early stages) combined with the notion of some technologies already having been introduced but not yet developed, the range is set from 2000 until the final 2030.

The second category is the economies of scale. Economies of scale are modelled through a learning curve here, meaning there are two main parameters that can be varied: the learning curve period and the progress ratio. The learning curve period represents the time it would take for a technology's cost to change and the progress ratio is the ratio of final to initial costs that can eventually be realised. For technologies early in development, the learning curve period can reach periods of just a small portion of the estimated technology's lifetime (Alberth, 2008). The learning curve period is by reviewing historic developments and forecasts (San Román et al., 2011; Schubert et al., 2014), roughly estimated at a range of 2-4 years. The progress ratio is for similar reasons set to be able to decrease the final price by 70% at most, approximating similar cost development projections for BEV retail prices, and expecting it to be able to decrease by 50% the least, giving us an uncertainty range of 0.5-0.7 for the progress ratio. The values are both very uncertain as it is not possible to extract the estimations from the given literature numerically. Therefore again iterative testing of the learning curve parameters have been an essential part of the range estimation, setting the ranges in such a manner that they still influence the system dynamics slightly when at their minimum, but strongly influencing the system dynamics when at their maximum levels. Due to the high level of uncertainty these rather large ranges have been selected.

The charging speed learning curve parameters are another identified uncertainty category. This uncertainty category has the same parameters as the economies of scale effect, since it is the same structure. Because of the learning curve being part of the same product, the EV charging station, the learning curve period is set at an equal range of that of the economies of scale learning curve period: 2-4 years. The progress ratio however is estimated to be slightly lower since the charging speed also depends on the battery technology of BEVs (Schubert et al., 2014; Tilindis and Kleiza, 2017). The progress ratio is therefore set with an uncertainty range of 0.3-0.5. Again, very much uncertainty lies with the estimation of these parameters, therefore an iterative process focussed on maintaining a large range has been a fundamental part of the determination of the ranges.

The investment acceleration difference is implemented by adding a so-called NWC public incentive investment boost. The boost is added to the maximum investment rate AIR_{max} of the NWC in equations 4.2-4.4. The maximum investment rate of commercial parties is set at 2 (Section 4.2.1), therefore the boost has been estimated to expand the maximum possible investment rate to a maximum of 150% of the commercial rate, giving it a range of 0-1. Another small addition is made to the initial market share: historical data does not show the initial market share rates for the EVCS market, therefore the initial market share is assumed to be uncertain. Differences in initial market shares can highlight investment behaviour in early stages of the market development, therefore this variation is expected to be a valuable addition the model's exploratory value. This has been set as an entirely uncertain range of 0-100%.

The risk valuation differences are incorporated through a risk premium ratio in the risk valuation process. The risk premium ratio of NWC determines what portion of the commercial risk premium valuations the NWC will maintain. To allow a complete picture of its influences, the ratio range has been set to 0-100%.

The final category is the profit target difference between the NWC and the commercial parties. This has been implemented similar to the risk premium ratio: a ROI aim ratio for NWC is added to the ROI aim input for market parties. The difference is relevant rather than the actual values, therefore the commercial ROI aim is fixed at a reasonable 10%, where the ROI aim ratio for NWC is varied from 0-100%.

A detailed overview is presented in Table 4.1.

Table 4.1: An overview of all uncertainties and corresponding parameter ranges, units, and superstructures.

Uncertainty variable	**Range**	**Units**	**Superstructure**
Alternative technology introduction year	2000-2030	Year	Alternative vehicle development
Alternative vehicle technology max attractiveness	0-8	Dmnl	Alternative vehicle development
Alternative vehicle development speed	0,05-0,35	Dmnl	Alternative vehicle development
BEV development speed	0,1-0,2	Dmnl	BEV development
Risk premium ratio NWC	0-100	%	Investment behaviour NWC
ROI aim ratio NWC	0-200	%	Investment behaviour NWC
NWC public incentive investment boost	0-100	%	Investment behaviour NWC
ICE average fuel price	0,80-1,60	€/l	Vehicle cost per km
Initial market share NWC	0-100	%	Initial active EVCS
Learning curve period EVCS cost	2-4	Dmnl	EVCS cost reduction learning curve
Progress ratio EVCS cost	0,5-0,7	Dmnl	EVCS cost reduction learning curve
Learning curve period charging speed	2-4	Dmnl	Charging speed reduction learning curve
Progress ratio EVCS charging speed	0,3-0,5	Dmnl	Charging speed reduction learning curve

4.7. Policy options

The 5 alternative that have been identified in Section 3.5 are used for policy implementation. The no policy base case is the reference case which logically needs no further implementation. However, other policies have been implemented in ways that the option of having no policy in the model will be preserved.

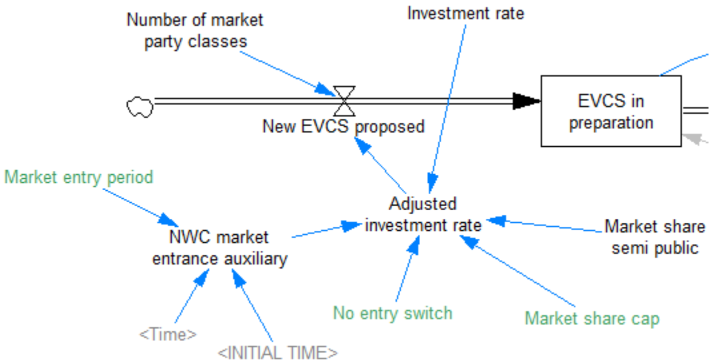


Figure 4.3: A snapshot of the policy levers Market entry period, No entry switch, and Market share cap in Vensim.

The full market entry restriction has been implemented as a switch that can be turned on and off. When the switch is on, the investment rate of NWC will be switched to 0 instantly from the beginning. The temporary market entrance is implemented as a lever that can range from 5 to 20 years, indicating the period in which the NWC is allowed to participate on the market. Due to the "no entry" alternative, the lower bound of the range is set to 5 years to ensure different effects of these two policy options, and the upper bound is set to 20 years because that is the final time in the model. The market share cap has been implemented as a lever with range 0-1 to be able to experiment through the entire possible range, where 0 is a market share cap set at

0% and 1 is a market share cap at 100% market share of NWC. For the implementation of these levers, several auxiliary variables have been used to include them in the EVCS development structure. Figure 4.3 shows how the levers are connection in the model.

Shareholder activation is implemented as a switch directly connected to the risk premium estimations of the market parties. When the switch is on, it overrides the risk premium ratio uncertainty and sets the risk premium of NWC equal to that of the commercial parties. A delay has been added to simulate the process of the shareholder actually being activated. A detailed overview of all policy levers is presented in Table 4.2.

Table 4.2: An overview of all policy levers and corresponding ranges, units, and superstructures.

Policy lever	**Range**	**Units**	**Superstructure**
Market entry period	0-30	Year	NWC investment rate
No entry switch	0,1	Binary switch	NWC investment rate
Market share cap	0-100	%	NWC investment rate
Shareholder activation switch	0,1	Binary switch	NWC risk valuation

4.8. Formalised model

Concluding the formalization of the model, the model can be shown in an XLRM structure by Lempert (Lempert et al., 2003). Corresponding uncertainty, lever ranges, and output units are included in figure 4.4.

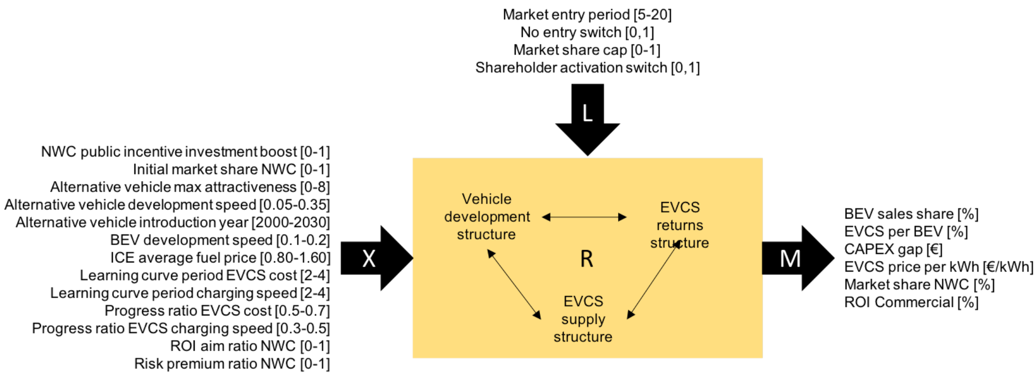


Figure 4.4: The formalized model shown in XLRM representation.

5

Model verification & validation

After formalisation of the model, the next step is to verify and validate the model. A model should be developed for a specific purpose and its validity with respect to that purpose is to be determined. First, the verification will be discussed: is the computerized model error-free, and properly implemented on suitable media. Second, the validation will be discussed. Since a proper validation process is an integral part of the modelling process itself, it should be noted that a significant portion of validation is already addressed by argumentation in Chapter 4, however additional stand-alone validation methods will be elaborated in this chapter.

5.1. Verification

The model has iteratively been traced and walked through during the modelling process to verify the functionality of each model structure and auxiliary calculation. Since the intended calculations are already presented in Chapter 4, the verification process itself will be discussed here per fundamental model structure. Prior to the structural verification, the used software will briefly be discussed.

The used software for the base model is Vensim DSS. Vensim is recognized software for developing, analysing, and packaging dynamic feedback models, and is a commonly used tool for the application of System Dynamics (Sterman, 2000). The model experimentation has been performed by using the EMA workbench in Python by Jan Kwakkel (2017). The used programmes are all high-level programming languages which are specifically designed for situations similar to the intended purpose, and therefore the programmes are considered to be highly suitable for this research. Additionally, the programme designs contribute to generating error-free models as well, for any error will be logged and/or reported to the user. The Vensim interface enables relatively easy verification of the base model because it captures all constants, auxiliary variables, levels, and rates as single variables with its own value or calculation defined by the modeller, as well as drawing clear arrows when a variable's calculation involves other variables. During model generation, all necessary constant values have intentionally been captured in individual variables to prevent used values to be hidden in any of the model views. Following these rules allowed me to continuously prevent or correct model errors as well as ensuring model flexibility which is desired for making the model suitable for dealing with uncertainties.

The EVCS supply structure has been traced by comparing the outcomes with the underlying theories. The project initiation process which is driven by variations in ROI and the maximum aggregated investment responsiveness of network companies is checked for consistency. The calculation outputs are all observed to be correct by comparison with manual calculations on single time steps, plus the variations are traced by monitoring the effects at different settings. The product life cycle process through levels and rates (proposal - realisation - decommissioning) is verified by tracing each variable in the chain while ensuring that parallel processes don't interact. Feedback dynamics such as active charging stations influencing the investment rate, which influences the active charging stations eventually through a series of delays, is traced by verifying every individual calculation in the process.

The vehicle development structure has 3 main structural designs: the traffic cycle, the vehicle sales distribution, and the sigmoid curves that are used to represent technology development estimations. All structures are traced elaborately to eliminate errors, while verifying that certain input values create the intended output. The sigmoid curves are both initially tested, as well as the responses of consecutive variables to their dynamic behaviour. No possibilities for errors are observed in the final version of the model, with regard to possible variation of uncertainties.

The returns structure is tested similarly and no errors have been found. The ROI calculation is compared with manual calculations on a single time step, the learning curves are simulated multiple times to verify intended effects of its parameters, and the market price calculations are extensively reviewed for consistency and responsiveness to its inputs. Again, no errors or irregularities are found. Finally, the general model structure has continuously been monitored to verify the effects of supply and demand rates on the market price and vice versa.

5.2. Conceptual model validation

Conceptual model validity determines that (1) the theories and assumptions underlying the conceptual model are correct and (2) the model's representation of the problem and the model structure, logic, mathematical and causal relationships are "reasonable" for the intended purpose of the model (Sargent, 2013). For the first statement, Chapters 3 and 4 cover all argumentation concerning the chosen conceptualisation of the system and logic behind chosen underlying theories and assumptions. The second statement is addressed here by comparison with by applying Face Validity: Relevant experts are asked whether the model's or substructures' behaviour is reasonable.

The general model structure (the supply demand structure via price variations) is a highly aggregated theoretical structure designed by renowned System Dynamics expert John Sterman. The structure is therefore assumed to be highly suitable for SD usage and the structure dynamics have been validated for this research through literature exploration and discussions with experts. The main theories behind the structure fundamental SD-related aspects are discussed with SD-expert Willem Auping (Interview TU Delft: Appendix A), and the relation to the real-world has been comprehensively discussed with energy policy experts at the Ministry of Economic Affairs and Climate Policy (Interviews Ministry of EA&CP: Appendix A).

Additional underlying and more detailed structures are all included separately, and therefore validated separately as well. The EVCS supply structure has again been validated through a series of discussions with Willem Auping, and also investment behaviour dynamics are considered to be reasonable and appropriate for the intended analyses. The vehicle development structure is discussed with officials from both the Ministry of Economic Affairs and Climate Policy and the ACM (Interviews Ministry of EA&CP and ACM: Appendix A), and the specific implementation of the structure is concluded to be reasonable and suitable for the intended research. Finally, the learning curves in the returns structure are a direct result of formerly mentioned discussions, while the remaining aspects of the returns structure are both suggested and validated by State-shareholderships experts at the Ministry of Finance (Interviews Ministry of Finance: Appendix A).

5.3. Operational model validation

Operational model validation is done by following recommendations by Sargent (2013): iterative testing and comparison throughout the modelling phase, accompanied by two additional methods: extreme conditions test, and output exploration and comparison to other research and models. The extreme conditions test will be discussed here, whereas the exploration and comparison will be done later in Chapter 6 during the analysis.

The extreme conditions test is done by varying the model's constant values largely in order to check whether erroneous behaviour occurs. The model structures are considered to be valid when plausible behaviour is still occurring after assigning extreme values. Plausible in this context is not to be confused with the notion of outcomes being realistic: plausibility is assumed when the output behaviour is logical considering the extreme conditions. Constants are set at -20% and +20% relative to their assigned values as shown in Appendix B.2. Key structural output variables are measured at all settings and checked for irregularities or errors which would indicate that the extreme values set lie beyond the model's operational boundaries. A summary of the extreme conditions test outcomes is shown in figure 5.1, presenting the measured variables with their corresponding observations. No errors or irregularities have conclusively been observed and all structure behaviours are found to be consistent to the intended behaviour as described in Chapter 4.

Table 5.1: Operational model validation: Extreme conditions test observations. Key structure outputs are monitored under extreme conditions (constants varied at -20% and +20% relative to their assigned values) and checked for errors and irregularities. Boundaries are stated to be found when errors occured, noticable observations are added for completeness.

Key structural output variable	**Superstructure**	**Boundary reached at settings**	**Additional Comments**
Aggregated investment responsiveness	Investment rate	None	
Investment rate	Investment rate	None	
EVCS in preparation	EVCS product life cycle	None	
Active EVCS	EVCS product life cycle	None	
Traffic	Traffic development	None	
Traffic replacement	Traffic development	None	
Vehicle Sales Distribution	Vehicle attractiveness	None	
Technology attractiveness ratio	Vehicle attractiveness	None	
Sigmoid curve outputs	Multiple	None	Boundaries lie at negative parameter values which are unable to occur due to factor and model settings.
EVCS price per kWh	Price	None	
Annual costs	Investment returns	None	
Annual net profit per EVCS	Investment returns	None	
Return on investment	Investment returns	None	
Learning curve outputs	Multiple	None	Boundaries lie at negative parameter values which are unable to occur due to factor and model settings.

5.4. Data validation

Finally, the model constants have been validated by following literature and data sources. Most data used is up-to-date and derived from official bureaus such as the Dutch CBS, LPB, and CPB, and the European IEA. Other constants that represent ratios or parameters are mainly derived from academic literature. Corresponding sources for all inputs are included in Appendix B.2. The mentioned bureaus are considered to be objective and reliable and therefore input data is assumed to be accurate and realistic.

6

Base case analysis

In this chapter, the base case will be analysed, The base case serves as a reference outcome of the model, which in this case consists of the outcome ensemble of the model when no policy is implemented. The chapter is structured by starting with a brief presentation of the experimental set-up (which is a recap of the primary model settings and the no policy situation in specific), followed by the steps as presented in the research framework: exploration, Sobol sensitivity analysis, and time series clustering. Finally, the results of this chapter will be concluded in the final section.

6.1. Experimental setup

The following settings have been used to represent the no policy base case. Info and references about the initial values of these variables can be found respectively in Chapter 4 and Appendix B. First, the uncertainties are briefly presented. Note that some of the ratios are implemented as ratio values instead of full percentages. A range value of 1 equals 100%.

Uncertainties

- Alternative technology introduction year (Range: 2000-2030)
- Alternative vehicle technology max attractiveness (Range: 0-8)
- Alternative vehicle development speed (Range: 0,05-0,35)
- BEV development speed (Range: 0,1-0,2)
- Risk premium ratio NWC (Range: 0-1)
- ICE average fuel price (Range: 0,80-1,60)
- ROI aim ratio NWC (Range: 0-2)
- NWC public incentive investment boost (Range: 0-1)
- Initial market share NWC (Range: 0-1)
- learning curve period EVCS cost (Range: 2-4)
- learning curve period charging speed (Range: 2-4)
- Progress ratio EVCS cost (Range: 0,5-0,7)
- Progress ratio EVCS charging speed (Range: 0,3-0,5)

As concluded from Chapters 3 and 4, the most important metrics of interest are the market price for EV charging, capital expenditures, ROI's of commercial market parties, EV sales rates, market shares, and the amount of charging stations per BEV. For exploratory reasons, the actual BEV shares in the vehicle mix are included throughout the exploratory phase. The following key performance indicators are registered as followed, with corresponding unit definitions:

Key Performance Indicators (KPI)

- BEV sales share: Registered as a ratio from 0-1, where 1 represents 100% BEV's in the vehicle mix.
- EVCS per BEV: Registered as a ratio from 0-1, where 1 represents a coverage of 1 EVCS per 1 BEV.

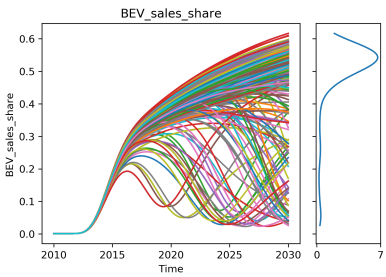
- CAPEX gap: Registered in €, where the number represents the difference in CAPEX for commercial parties compared to NWC. A positive number is a higher CAPEX for commercial parties than NWC, and vice versa.
- EVCS price per kWh: Registered in €/kWh, representing the charging fees.
- Market share NWC: Registered as a ratio from 0-1, where 1 represents a 100% market share of NWC.
- ROI Commercial: Registered as a ratio value without boundaries, where 0 represents the break-even point and 1 represents 100% returns expected to be realised by commercial parties on a new EVCS project.

All outcomes are captured as full time series outcomes over a period of 20 years (2010 - 2030). The experimental design is generated using Latin Hypercube Sampling (LHS). LHS is a statistical method for generating near-random samples of parameter values from a multidimensional distribution. LHS works very well for computational experiments for it adjusts this distribution to the previously taken samples and making sure that the samples taken are always evenly distributed over all parameter ranges. Although there are no strict requirements for determining experiment counts, a decent coverage of results is simulated by taking 1000 different scenarios. This set of outcomes will also be used for time series clustering.

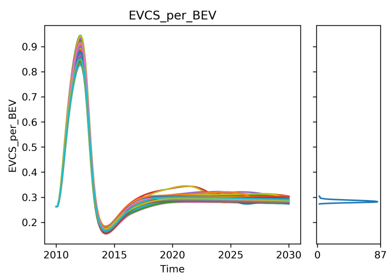
For the Sobol sensitivity analysis, a specific Sobol sampling method is used. The Sobol technique requires a larger amount of experiments, determined by taking the original set of scenarios n, and increasing it relative to the amount of predictors p into $N = n(2p+2)$ samples. This implies $1000 \times (2 \times 13 + 2) = 28000$ scenarios.

6.2. Base case exploration and operational validation

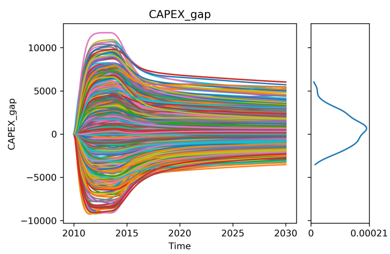
First, the initial outcomes will be explored. This will be done by generating line-plots of all outcome cases and present them in a combined graph. Additionally, a density plot is added along the same y-axis of the line-plot to illustrate the distribution of all case outcomes over the y-axis. This gives us a first understanding of the range, potential troubling developments, and the robustness of the outcomes. Figure 6.1 shows all KPI line-plots with corresponding density plots.



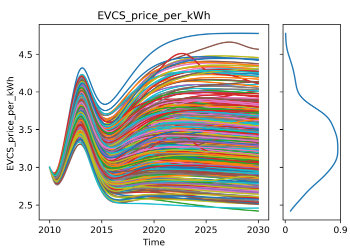
(a) BEV sales share [ratio 0 - 1]



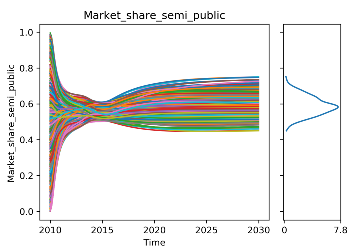
(b) EVCS per BEV [ratio 0 - 1]



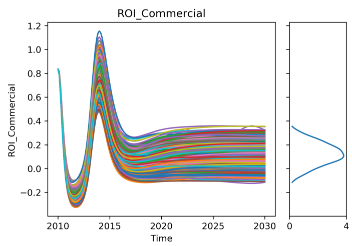
(c) CAPEX gap [€]



(d) EVCS charging price [€/kWh]



(e) Market share NWC [ratio 0 - 1]



(f) ROI Commercial at [ratio 0 - 1]

Figure 6.1: Lineplots of the complete outcome space of all performance indicators at no policy. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

The BEV sales share (figure 6.1.a) shows a wide range of possible outcomes, but the density plot shows relatively few cases below a sales share of 0.5. This indicates that of the outcomes are scattered but little variance is expected. Remarkable is that all cases that go downwards still recover going upwards after a certain period. This means that even though there is a risk of BEV penetration being disturbed, BEV sales generally increase on the long term. BEV sales share is therefore expected to be sensitive only to few specific values of input parameters. The overall behaviour of BEV sales seems realistic: electric vehicle outlooks and forecasts from both IEA and Bloomberg suggest that for consumer's, electric vehicles will equal ICE attractiveness around 2025 (Finance, 2018; IEA, 2017). Figure 6.1.a shows a strong mean around 0.55 in 2030 which lies around 0.5 in 2025, which means consumer choices are equally distributed amongst BEV and its alternatives (in this case mainly ICE). Conclusively, the BEV sales share is relatively robust: the vast majority of scenarios results in similar increase of BEV sales shares.

EVCS per BEV (figure 6.1.b) shows very robust behaviour: all cases have a very sharp peak in the beginning and a short negative bump below 0.2 right before the system settles down around the .25 equilibrium level. The sharp spike on the density plot also shows that this outcome variable is very insensitive to all uncertainties in the model: little variance can be registered and not a single significant deviation to the average behaviour is spotted. Conclusively, with no policy applied, the demand for EVCS is sufficiently satisfied (all values are mostly higher, and in a short period relatively close to the reference ideal value of .25=25%). The model suggests the market to settle down after about 10 years, which seems long but since the the EVCS market in the Netherlands situation seems to be settling down currently in 2018 (Interviews Alliander, Ministry of EA&CP: Appendix A), this can also be seen as an acceptable representation of the system.

The CAPEX gap outcomes indicate cost advantages for network companies: values indicate how much higher capital expenditures are for commercial parties when compared to network companies. The results (figure 6.1.c) are remarkably symmetrical. Although the density plot is very slightly shifted to the positive side, it seems that there are almost as many cases that follow a negative course as a positive course in an exact mirrored behaviour. Additionally, the spread is quite wide and the distribution of cases is similar to a normal distribution. These observations combined with the meaning of the CAPEX gap (differences in capital requirements) imply significant sensitivity to uncertainty. This KPI is an important indicator of capital advantages, meaning it will be essential to investigate its main drivers, with a focus on distinguishing uncertainties in NWC behaviour from general market uncertainties.

The EVCS charging price (figure 6.1.d) shows a very wide and distributed spread in its outcome space. A broad normal distribution with a subtle tail on the positive side on the density plot supportively highlights the high sensitivity of this KPI to the uncertainties in the model. When looked closely, some differences in behaviour can also be spotted after 10 years (year 2020). The EVCS charging fee is an important indicator of market development, therefore its sensitivity implicates a clear risk of the undesired market development due to uncertainties since a considerable portion of cases increase on the long term. Again, it is important to distinguish NWC behavioural uncertainty from general market uncertainties in further analyses. Value development generally agrees with existing literature and predictions (Schroeder and Traber, 2012; Serradilla et al., 2017).

The market share of network companies (figure 6.1.e) generally finds a clear equilibrium that settles right after about 10 years (at 2020), regardless of its initial value. Its initial value is a logical direct consequence of the initial value uncertainty parameter, but it does show interesting behaviour around 2015: although not yet entirely clear during exploration, it appears that many initially low market shares tend towards high market values on the long term and vice versa. This phenomena will be examined further in the Sobol sensitivity analysis and through time series clustering. The outcomes also show a clear skewed distribution with about 60% market share as its mean, indication that the vast majority of the cases result in a dominant presence of NWC's on the market. No existing data is found to compare these results, however the distribution around 60% are realistic and logical when considering how market party classes are defined and implemented in the model: two composite actors with similar behaviour, slightly varied by investment behaviour advantages of network companies.

The expected returns of commercial parties (figure 6.1.f) develop in a trajectory similar to the EVCS price per kWh, but the cases diverge significantly less on the long term. Yet still a relatively large spread is seen (from nearly -0.2 to almost 0.4 in the end state). The majority of the cases show positive results from 2013 onwards, which is a positive sign: most of the cases develop in a positive business case for commercial parties. However, still a number of cases settle below the 0.0 line, indicating a deteriorating business case for commercial parties. The peak of the density plot also lies around 0.1, which is not very high considering that the model generates prices based on marginal costs. Aside from the high initial value, the behaviour shows a typical market development routine: low values in the beginning, making the market not particularly attractive, then a rise that facilitates the markets growth phase, followed by reaching an equilibrium around the break-even point. The initial value is most likely the effect of a shortage of EVCS per BEV or a high initial EVCS charging price.

Conclusively, the most complex results are found with the CAPEX gap, EVCS price per kWh, the market shares and the returns for commercial parties. The EVCS per BEV is very robust and therefore it can be excluded from further analysis. The BEV sales share still has a large variation and therefore will be examined further to determine its most influencing parameters. Overall the model shows acceptable and sufficiently realistic behaviour.

6.3. Sensitivity analysis

The following section will comprehensively describe the model sensitivity analysis using Sobol indices. All selected KPI's from the previous section will be examined, focussing on main effects $S1$ and total effects ST (Section 2.4.1). Because Sobol indices are calculated at a certain point in time and the behaviour of the system is significantly dynamic, various points in time will be selected per outcome based on outcome plots from figure 6.1. Factor prioritisation will be done: most relevant input parameters will be prioritised for further analysis through time series clustering. Since the experiments and outcomes datasets are readily available for time series clustering hereafter, factors don't really have to be "fixed" but non influential factors will be excluded from further analyses. Thus, factor fixing will be referred to as factor exclusion instead in the following sections.

6.3.1. Sobol indices

For each outcome variable, the $S1$ and ST of every uncertainty on that outcome variable is calculated. A high $S1$ means the direct effect of a certain uncertainty on the corresponding performance indicator is high, and when ST is significantly higher this means that interaction effects are significantly dominant. A 95% confidence interval is also considered for each $S1$ and ST. Significant added effects of interactions between uncertainty parameters is concluded when the confidence interval of ST lies completely outside of that of $S1$, and the initial values of the indices are high. When needed (interaction effects are significant and no obvious explanation can be deduced from the model structure), further examination will follow by looking into second order effects $S2$.

Based on characteristic moments concerning the behaviour of the outcomes, different points in time have been analysed. For example the BEV sales share shows quite consistent behaviour on the short-term (until 2020), and diverges on the long term towards 2030. Overall the outcomes' bahaviours can be split into two different parts: short-term and long-term behaviour. From 2010 to 2020, all outcome behaviours are highly dynamic and after 2020 the values stabilize (with the exception of BEV sales share which shows opposite behaviour in some cases). Also variance in case results is relatively consistent during the first 10 years and during the final 10 years. Detailed calculation of Sobol indices on several points in time support these findings and therefore the index results will be presented here by showing combined short- and long-term outcomes separately. Detailed plots for specific relevant moments in time can be found in Appendix C.1. First, the short-term outcomes are shown by taking all $S1$ and ST values at 2012, 2014, 2016, 2018, and 2020, and presenting the averages in figure 6.2.

Before discussing the outcomes, the unimodality and symmetry of the outcomes should be considered. As shown by the density plots in figure 6.1 all outcomes have only 1 clear peak in the distribution, indicating that all outcome variables are unimodal. Symmetry however is not collectively present: the BEV sales share has a long tail and the EVCS price per kWh is a bit skewed towards lower values. Since the deviations are little and distribution are still unimodal, Sobol sensitivity analysis outcomes are assumed to be meaningful, however for BEV sales share and EVCS price per kWh the outcomes should be used cautiously.

The outcomes will be discussed from left to right, starting with the EVCS price per kWh. The more influential factors are highlighted in figure 6.2 by colour. A first glance highlights the considerably dominant impact of the ROI aim ratio of network companies on the EVCS price differences on the short-term. The second most influential uncertainty parameter is the learning curve period EVCS cost. The main effects of these variables are respectively 0.6 and 0.2, while all others score below 0.10 on the Sobol indices. Total effects ST are almost

	EVCS price per kWh		BEV sales share		Market share semi public		ROI Commercial		CAPEX gap	
	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1
Alternative technology introduction year	0,0006	0,0010	0,2861	0,1627	0,0033	0,0024	0,0003	0,0002	0,0007	0,0003
Alternative vehicle development speed	0,0008	0,0018	0,0502	0,0291	0,0042	0,0020	0,0014	0,0009	0,0010	0,0008
Alternative vehicle technology max attractiveness	0,0005	0,0005	0,2060	0,0545	0,0033	0,0024	0,0003	0,0004	0,0007	0,0003
BEV development speed	0,0004	0,0008	0,1451	0,1434	0,0033	0,0024	0,0002	0,0002	0,0007	0,0003
ICE average fuel price	0,0004	0,0008	0,4471	0,4458	0,0033	0,0023	0,0002	0,0000	0,0007	0,0003
Initial market share NWC	0,0326	0,0188	0,0005	0,0006	0,2975	0,2978	0,3856	0,3451	0,9921	0,9682
NWC public incentive investment boost	0,0202	0,0210	0,0003	0,0004	0,5831	0,5841	0,0646	0,0646	0,0037	0,0030
Progress ratio EVCS charging speed	0,0003	0,0008	0,0004	0,0003	0,0033	0,0024	0,0002	0,0001	0,0007	0,0003
Progress ratio EVCS cost	0,0771	0,0784	0,0002	0,0003	0,0036	0,0025	0,0559	0,0518	0,0027	0,0001
ROI aim ratio NWC	0,6173	0,6031	0,0020	0,0024	0,0032	0,0023	0,2649	0,2546	0,0006	0,0001
Risk premium ratio NWC	0,0876	0,0811	0,0007	0,0001	0,1272	0,1261	0,1324	0,1273	0,0031	0,0025
learning curve period EVCS cost	0,1926	0,1898	0,0002	0,0002	0,0063	0,0024	0,1338	0,1283	0,0090	0,0133
learning curve period charging speed	0,0002	0,0004	0,0008	0,0010	0,0028	0,0021	0,0004	0,0010	0,0006	0,0000

Figure 6.2: Sobol indices for all outcomes on the short-term. Values are shown by outcome variables (columns), Sobol index (sub-columns), and uncertainties (rows). Short-term refers to combined index outcomes from 2010-2020. Colours highlight the effects of the variables: higher values are darker and cells become purple when more significant (starts from above 0.10).

equal to the main effects $S1$, indicating that interaction effects are less influential than direct effects. The ROI aim ratio of a network company represents the ability of a network company to have lower profit targets than commercial parties. The dominant impact shows how strong the effects of profit targets are on price developments. The target ROI for market parties in essence determines a certain mark-up on the ROI which is used to determine market prices for new EV charging stations. What eventually happens when the ROI aim ratio is adjusted, is that the network companies (who own roughly 50-60% of the market as observed from figure 6.1.e) set lower market prices, with a maximum difference of 10%. This clearly has a very strong effect on resulting market prices, which is most likely supported by the rapid increase in absolute supply on an emerging market such as the EV charging infrastructure market. A second, considerably less but still very significant, influential parameter is the learning curve period EVCS cost. This implies a strong influence of learning curve in the short-term when the learning period is varied. A learning curve is expected to show most influence on longer-terms because of its accumulating dynamics. The learning curve eventually strongly influences the prices because it lowers the capital expenditures for new EV charging stations. The learning curve period's scores here thus show that the cost development period significantly determines whether short-term impacts on charging fees are possible due to learning. As stated before, the results of this outcome must be interpreted cautiously due to slight asymmetry of the outcome distribution. In this case, the high scores of the mentioned parameters allow the assumption that the found results are meaningful, but additional values below 0.1 will be neglected to prevent insignificant conclusions.

The BEV sales share indices do show very interesting and clear results. First of all, the total effect scores clearly show that the only relevant influences come from variables that are part of the vehicle development structure: alternative vehicle development parameters, BEV development speed, and ICE average fuel price. Second, the importance of interaction of the alternative vehicle development parameters is shown by the fact that total effects are considerably higher than main effects. When second order values are evaluated (Appendix C.1), it shows that especially the maximum attractiveness and the introduction year together explain a considerable portion of the total variance. The results are very useful, since the vehicle development structure simulates the vehicle market itself. The BEV sales share here being influenced solely by the parameters that are part of the vehicle market indicates that BEV rates are significantly independent of the development of the EV charging infrastructure market on the short-term.

The market share initials are determined by the input settings of the direct initial, but figure 6.1.e shows an interesting tipping point around 2015 where outcomes not only converge but seem to crossover from high to low values compared to the mean or vice versa. As verified in figure 6.2, the early values are dependent of the initial settings, but risk perception differences and predominantly investment responsiveness (investment boost) are accounted for the other significant portion of variance on the short-term. The investment boost simulates the possibility of network companies being able to respond more aggressively to market signals: when ROI estimations are positive, the network company could invest more as a result of public incentive, made possible by the availability of sufficient financial capital. Investment behaviour therefore appears to have a very strong influence on market shares on the short-term already. Since market shares stabilise quite early (figure 6.1.e), the short term results are most relevant and are considered to be decisive for the entire period. Other factors also show to be influential, but it can be concluded that when investment behaviour differences are larger, network companies will increasingly influence market power distribution.

The effects on the ROI of commercial parties are quite complex: the index values are moderate and multiple factors account for a considerable portion of the outcome variance. The initial market share does show to be most influential, indicating that initial market power distribution will affect short-term profitability of investing in charging infrastructure for commercial parties. All other variables that influence the profitability on the short-term are risk valuation differences, profit target differences, and cost reducing learning curve effects. The profitability is the most important metric for evaluating possible attractiveness of the market for commercial parties. The strong influences of market power distribution and behavioural differences with network companies imply that this attractiveness can be significantly disturbed by the activity of network companies on the market, when these parties have more favourable investment strategies. The earlier mentioned arguments of network companies to enter these emergent markets mainly suggested a network company to "push" the market initially by investing more aggressively than commercial parties (see Chapter 1). However, these results show that by doing so the profitability for commercial parties is influenced. This raises the conclusion that the proposed strategy could rather backfire because lowering profitability will postpone investment even further.

The variance in cost advantages for network companies, measured as CAPEX gap, is explained almost completely by the initial market share. A small portion of interaction effects also seems to be responsible for this effect, however the difference between ST and $S1$ is not significant (confidance intervals overlap). The cost advantages are therefore concluded to be completely dependent of initial market power distribution.

Next, the long-term sensitivity will be addressed. The Sobol indices will be used again, but now calculated at 2030 (the end-state). Figure 6.3 shows all outcomes. A first glance over the table already provides the idea that long-term outcomes are affected more distributed: more variables are found to be influential as indicated by the shaded cells.

The long-term effects of profit target differences between commercial parties and network companies on the EVCS price per kWh is considerably lower than they were on the short-term. The price development is mostly influenced by the EVCS cost learning curve parameters, with specific emphasis on the learning curve period. The difference between short- and long-term sensitivity is interesting and provides essential insights for a decision-maker when choosing a role demarcation strategy: short-term performance is mainly influenced by differences in market party behaviour, whereas long-term results are predominantly affected by underlying market characteristics. This could imply role demarcation policy measures to mainly affect short-term outcomes, suggesting that these measures should be aimed at short-term goals only.

The BEV sales share is on longer terms almost completely dependent of the possible breakthrough of an alternative vehicle technology. Even vehicle development parameters like BEV development speed and ICE average fuel price are now accounted for a very limited portion of outcome variance. Uncertainties belonging to other structures are increasingly influential, but still very low scores on the Sobol indices remain. Further assessment of second order effects (Appendix C.1) shows that the interactions between all 3 alternative vehicle development parameters is the most important factor influencing final BEV sales shares, where the interaction of the introduction year and the maximum attractiveness alone already accounts for 30% of the variance.

Possible risk valuation differences are predominantly responsible for the variance in market shares on the

	EVCS price per kWh		BEV sales share		Market share semi public		ROI Commercial		CAPEX gap	
	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1
Alternative technology introduction year	0,0101	0,0034	0,6317	0,2149	0,0015	0,0014	0,0059	0,0005	0,0025	0,0011
Alternative vehicle development speed	0,0029	0,0004	0,1591	0,0067	0,0019	0,0003	0,0052	0,0023	0,0015	0,0005
Alternative vehicle technology max attractiveness	0,0103	0,0093	0,6638	0,2418	0,0016	0,0021	0,0055	0,0006	0,0025	0,0007
BEV development speed	0,0001	0,0002	0,0431	0,0409	0,0007	0,0017	0,0001	0,0002	0,0008	0,0002
ICE average fuel price	0,0001	0,0002	0,0015	0,0017	0,0007	0,0019	0,0001	0,0004	0,0007	0,0003
Initial market share NWC	0,0070	0,0073	0,0001	0,0003	0,3881	0,3571	0,1944	0,1890	0,9750	0,9424
NWC public incentive investment boost	0,0008	0,0010	0,0000	0,0000	0,1529	0,1494	0,0025	0,0010	0,0020	0,0014
Progress ratio EVCS charging speed	0,0001	0,0003	0,0012	0,0011	0,0007	0,0019	0,0001	0,0003	0,0007	0,0003
Progress ratio EVCS cost	0,2254	0,2232	0,0027	0,0031	0,0097	0,0023	0,0049	0,0027	0,0359	0,0000
ROI aim ratio NWC	0,2331	0,2270	0,0033	0,0026	0,0929	0,0268	0,5192	0,5183	0,0055	0,0009
Risk premium ratio NWC	0,0942	0,0910	0,0012	0,0011	0,4252	0,3890	0,2810	0,2759	0,0241	0,0199
learning curve period EVCS cost	0,4446	0,4390	0,0058	0,0039	0,0059	0,0027	0,0019	0,0016	0,0223	0,0160
learning curve period charging speed	0,0004	0,0011	0,0002	0,0003	0,0004	0,0007	0,0001	0,0002	0,0007	0,0002

Figure 6.3: Sobol indices for all outcomes on the long-term. Values are shown by outcome variables (columns), Sobol index (subcolumns), and uncertainties (rows). Long-term refers to end-state index outcomes at 2030. Colours highlight the effects of the variables: higher values are darker and cells become purple when more significant (starts from above 0.10).

long term. Compared to the short-term, risk valuation difference shows to have overtaken the investment boost effects.

The returns of commercial parties are most sensitive to the ROI aim ratio of network companies. The effects of the initial market share on the short-term are strongly decreased on the long-term, while differences in profit targets are now accountable for half of the variance. Possible advantages for network companies due to a lack of shareholder control or due to public values are also highly influential on the long-term: risk premium ratio accounts for a large portion of the variance as well. The earlier notion of investment behaviour differences to be disrupting profitability for commercial parties is not only supported on the long-term, but also much more relevant. The decrease of effects of initial market power distributions however imply that any final equilibrium is not necessarily influenced by these power distributions. This suggests the possibility for decision-makers to implement different short- and long-term strategies.

No significant difference between short- and long-term sensitivity is seen on CAPEX gap outcomes.

6.3.2. Sensitivity analysis conclusions

The sensitivity analysis has provided insights on what factors influence both short- and long-term outcome variance for all KPI's. For factor fixing, all uncertainties have shown relevant influence on at least one KPI in either the first or the final period of the simulated market development. No factors will be fixed, and only factor priorities for each KPI will briefly be concluded here.

Short-term price development is mainly influenced by differences in market party behaviour, whereas long-term results are predominantly affected by underlying market characteristics. More specific, profit aim targets are the main reason for shaping short-term price developments, meaning that when network companies invest on the market based on public values this will have a significant influence on price developments. After a longer period, economies of scale is most decisive for final outcomes. This last factor can not be influenced by decision-makers, but can and should be used and considered in the decision-making process because it might suggest that less parties on the market would be more efficient. However, role demarcation policy will probably mainly influence short-term price development.

The vehicle development system is concluded to develop significantly independent to the EV charging infrastructure market. The results have shown that most significant variance is explained by uncertainties on the vehicle market itself only on both the short- and the long-term. When choosing a certain market organisation strategy on this infrastructure market, electric vehicle rates should therefore not be considered as a criterion. Additionally, the cost advantages between market parties are only significantly influenced by market share initials.

Investment behaviour differences have a very strong effect om market power distributions on both the short- and long-term. Short-term market shares are most sensitive to differences in investment rates by commercial parties and network companies: more aggressive investment rates because of public incentives or the desire to "push" a market will result in network companies being most dominant on the market at first. Risk valuation differences later become most decisive: on the long-term the advantages of the stability and liquidity of network companies create a significant advantage on the market. Both represent important possible differences in investment behaviour, supporting the notion of network companies being unfair competition on the market.

The profitability for commercial parties is heavily influenced by profit target and risk valuation differences. Again this shows that commercial parties will be disadvantaged when network companies are actively showing different behaviour on the market. The further the market develops, the more learning curves influence the profitability as well. From a policy maker's point of view it is important to consider these results carefully: the strategy for network companies to stimulate the market on the short-term by investing aggressively in the early stages of the developing market can clearly backfire for it influences commercial parties' profitability significantly. Although a network company would boost the market itself, the network company itself as an incumbent would likely discourage commercial parties from entering the market.

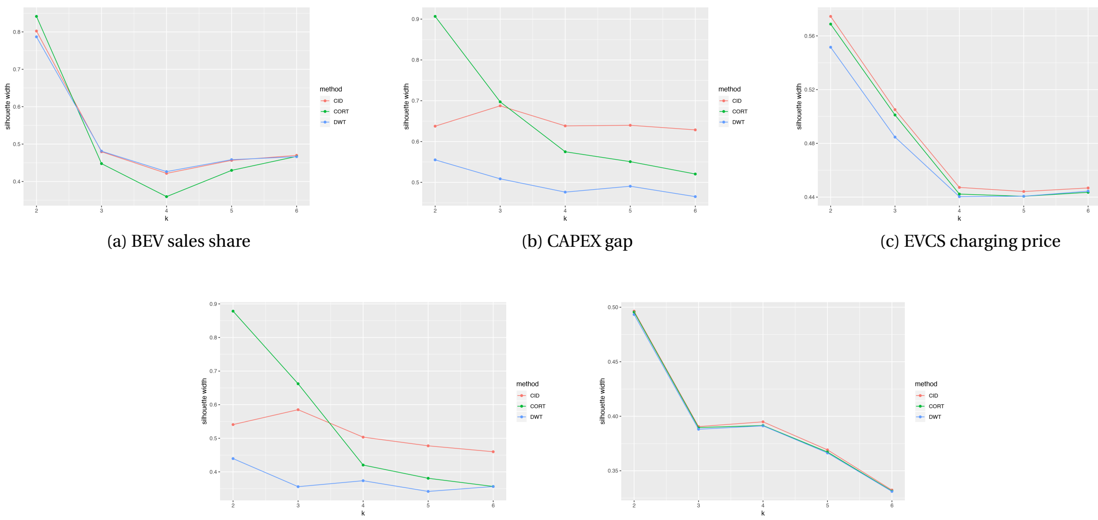
Investment behaviour differences appear to have a strong influence on market development, indicating the overall relevance of role demarcation policy and the importance of market organisation strategies. Market specific characteristics such as economies of scale or vehicle development factors also show to influence market development considerably, highlighting the complexity of developing future oriented strategies on role demarcation on developing markets. It is important for the decision-makers to consider what metrics are considered to be most relevant when developing a certain strategy.

6.4. Behaviour based scenario discovery

The next section describes the results of the time series clustering analysis. In the base case analysis, the results will be described comprehensively for a complete understanding of the process and the model behaviour. The 4 policy analysis steps as described in Section 2.4.2 are followed consecutively, where steps 1 and 2 combined are described in the clustering procedure (Section 6.4.1), and steps 3 and 4 are described in the clusters subspace analysis (Section 6.4.2), followed by the from time series clustering deduced conclusions ()Section 6.4.3). Bear in mind that although only final results and outcomes are presented, they are the result of an iterative process: cluster counts have iteratively been revised by running clustering procedures multiple times while visually assessing their corresponding clustered line-plots. The process is somewhat longer than it may appear, however is presented in a more concise form to increase readability by only presenting the essential.

6.4.1. Clustering procedure

The first step of time series clustering is to determine the cluster counts. This will be done by calculating silhouette widths, which indicate the validity of each cluster count k on a scale of -1 to 1. The general guideline is to pick the highest value for maximizing validity, however the final decision should be made by minor adjustments towards the modellers desire (Rousseeuw, 1987). To enable a clearer view, all clustering methods are used for calculating silhouette widths. The number of clusters chosen is then based on visual inspection of figure 6.1 and the combined highest silhouette width across all methods. Cluster counts from 2 up to 6 are used, for figure 6.1 suggests that higher cluster counts to be valid is highly unlikely.



(a) BEV sales share (b) CAPEX gap (c) EVCS charging price

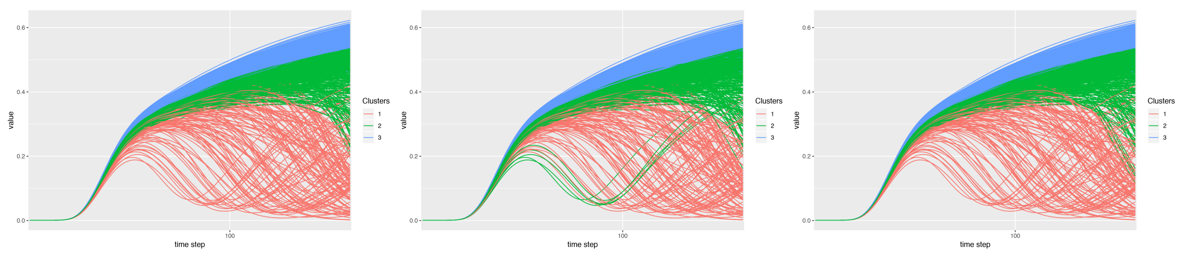
(d) Market share NWC (e) ROI Commercial

Figure 6.4: Silhouette widths of CID-, CORT- and DWT-generated cluster counts with k = amount of clusters at no policy.

BEV sales share shows by far the highest value at k=2. The ensemble plot in figure 6.1.a would suggest that the downward sloping behaviour will be separated from the continuously rising cases. At k=3 the silhouette width is for all methods just below 0.5, which remains a fair number. For enabling more detailed insights concerning BEV sales shares, k=3 clusters will be examined. The CAPEX gap silhouette widths vary more across different methods. CID validity increases slightly when going higher, only the CORT silhouette widths decrease strongly when higher than k=2, and higher values still show stable and high silhouette widths. Because of the symmetry of the ensemble in figure 6.1.b, the cluster count for CAPEX gap should be an even number and will therefore be fixed at k=4. The cluster count for EVCS price per kWh is, for similar reasons to the BEV sales share, settled at k=3. Market share is partitioned into 4 clusters determined by a small increase in validity for DWT, and ROI commercial will be clustered into 4 partitions.

Cluster counts per outcome variable:

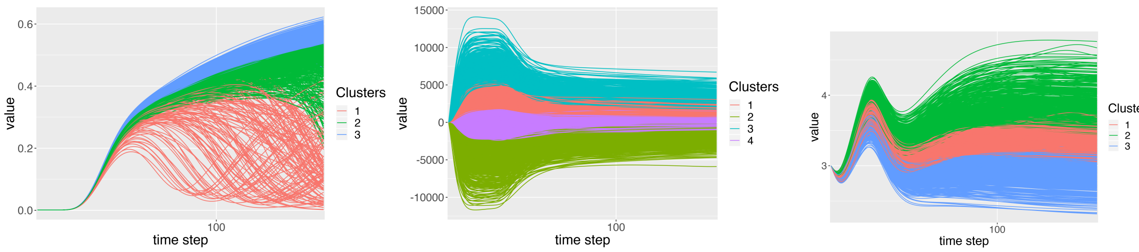
- BEV sales share: k=3.
- CAPEX gap: k=4.
- EVCS price per kWh: k=3.
- Market share NWC: k=4.
- ROI Commercial: k=4.



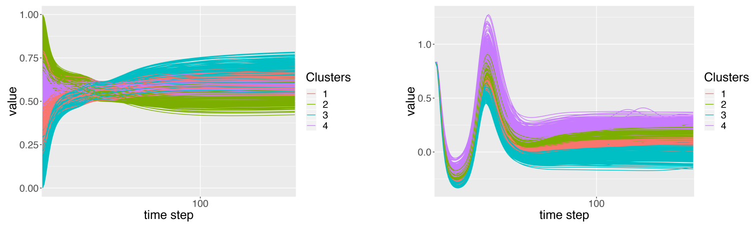
(a) CID (b) CORT (c) DWT

Figure 6.5: CID-, CORT- and DWT-clustered outcomes with k=3 clusters of BEV sales share at no policy.

The clusters are now generated with the defined k-values per outcome. First, all 3 clustering methods are applied for comparison. The clustering algorithms generally didn't show very strong differences (Appendix C), however CID performed slightly better than its alternatives. Figure 6.5 shows BEV sales share outcomes clustered with 3 different methods as an example. The CID-clustered partitioning is straight forward: cluster 1 (red) captures all cases that curve downwards somewhere on the long term, cluster 2 (green) captures all mid-valued outcomes, and cluster 3 (blue) captures all high BEV market penetration rates which all show steady increase until the end-state. Compared to the CID cluster designation, some flaws are observed when viewing the alternatives: CORT partitioning (6.5.b) seems to have clustered primarily on end states (e.g. see the green downward sloping line at the bottom of the ensemble), and DWT picks a slightly larger area for cluster 2 (green), adding some significantly decreasing values to the cluster. Additionally, reviewing the silhouette values of the different methods as shown in figure 6.4 shows a generally higher validity for CID-clustered partitioning. Because of the small differences in performance between the methods, CID is selected. The final clustered metrics of interest are shown in figure 6.6.



(a) BEV sales share [ratio 0 - 1], k=3 (b) CAPEX gap [€], k=4 (c) EVCS charging price [€/kWh], k=3



(d) Market share NWC [ratio 0 - 1], k=4 (e) ROI Commercial at no policy [ratio 0 - 1], k=4

Figure 6.6: CID-clustered outcomes with k clusters of all KPI's at no policy.

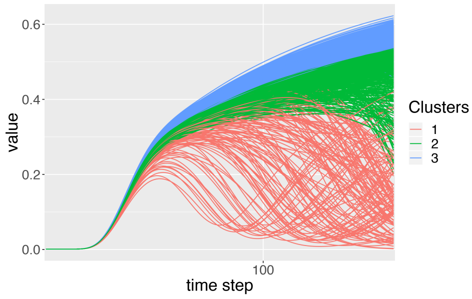
6.4.2. Cluster predictors

The generated clusters for each outcome variable are examined in this chapter with the goal to induce certain rules for cases to belong in a certain cluster. All 5 partitioned outcomes shown in figure 6.6 will be discussed in similar order. The outcomes are plotted into pairs-plots, which are basically collections of scatterplots in which all input variables plotted against all input variables, including against itself. The points within these scatterplots are marked correspondingly to the cluster memberships, enabling the analyst to induce generative rules from the boxes. The complete pairs plots are generated and shown in Appendix C, while the most interesting outcomes are presented in this section. The pairs plots are rather complex figures, but a first selection is made by a simple rule of thumb: when the clusters are presented in the pair plot boxes in a uniform distribution, there is no rule to be induced from these parameters or their interactions. For each outcome, each cluster most likely has somewhat different predictors. From initial visual analyses of the complete pairs plots (Appendix C.3), the most important predictors have been selected. These predictors' outcomes will be shown and evaluated here.

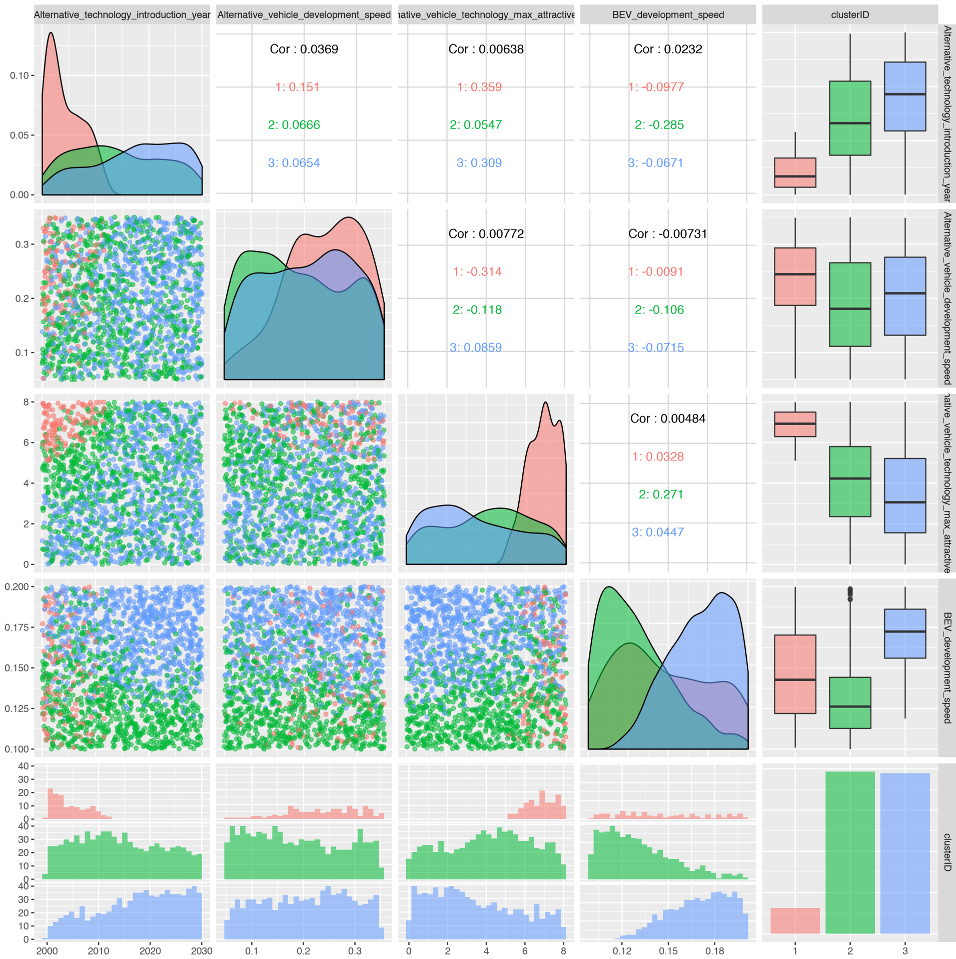
For the BEV sales share, the most important predictors are found to be the *alternative technology introduction year*, the *alternative technology development speed*, the *alternative technology max attractiveness* and the *BEV development speed*. Figure 6.7 shows influential input pairings and their cluster memberships: the diagonal cells show the density estimates of certain clusters across values of the predictor, the scatter plots to the left of the diagonal density graphs show the interaction effects of inputs by showing colour (cluster id) biases towards a certain direction, the histograms on the bottom show the distributions of cases per cluster id along the axis of the inputs indicated at the top of the figure, and the box-plots show the same distributions but represented by box-plots along the axis of the parameters indicated at the right of the figure.

First let's consider the clustered line plot and classify the clusters. Based on cluster characteristics, each cluster can be classified:

1. Red: BEV rates rise rapidly on the short-term, then decline after certain periods and rise again by rates similar to the decline.



(a) Clustered line plot



(b) Pairs plot

Figure 6.7: BEV sales share filtered findings through time series clustering at no policy. CID-clustered at $k = 3$.

2. Green: BEV rates rise rapidly on the short-term, then stabilize slowly into a moderate increase.

3. Blue: BEV rates rise rapidly on the short-term, then continue rising moderately but at a higher rate than that of the green cluster (2).

From the research point of view, the clusters can be ranked by desirability based on the rate of BEV sales increase: blue cluster 3 is most desirable, green cluster 2 is also desirable, but slightly less favoured than cluster 3 results, and the red cluster is the complete set of undesired outcomes. The input pairings in figure 6.7.b show the influences of the predictors, including their combined effects. To refer to certain cells, index-1 notation will be used: [row number, column number]. Cell [5,5] shows the distribution of cases among the different clusters. Similar to what is concluded from the density plots in the exploration phase, the clustering procedure has resulted in unequal clusters due to the low amount of cases that show the red cluster's behaviour. Although logical and seemingly accurate, this could cause difficulty when inducing rules from the analysis. Nevertheless, the figure shows some visible correlations between parameter values and cluster memberships. The goal is to look for non-uniformity in figures, indicating possible rules that determine cluster memberships.

The density graphs [1,1] and [3,3] both show clear "spikes" on one side for the red cluster. Both the green and the blue cluster are distributed across the parameter values, but the corresponding histograms at the bottom at [5,1] and [5,3] suggest a slightly skewed distribution of the more desirable cases towards the opposite side of the red spikes. However, when viewing the box-plots at [1,5] and [3,5], the boxes overlap and the means of the boxes are both within the boundaries of the other box. A basic rule of thumb for concluding significance in differences between datasets is that this overlap means no valid differences can be stated. The red cluster's distribution however does differ significantly from all other values, indicating a significant influence by the *alternative technology introduction year* and the *alternative vehicle max attractiveness* individually. More specific, it can be stated that when the *alternative technology introduction year* is higher than half of its parameter range or the *alternative vehicle max attractiveness* is lower than half of its maximum parameter range, the red cluster behaviour is completely excluded. A similar conclusions can be drawn regarding the separation of the green and the blue cluster, indicated by cells [4,4], [4,5], and [5,4]: The green and the blue cluster are separated by respectively low and high values for BEV development speed. No valid statements can be made regarding the *alternative vehicle development speed*.

Further assessment of the influencing factors can be done by viewing the pairings of the parameters. The paired plot in [3,1] shows almost a nice gradient diagonally from the upper left corner towards the lower right corner, flowing from red, to green, to blue. The upper left corner is clearly dominated by the red cluster, indicating that the combination of low values for *alternative vehicle introduction year* and high values for *alternative technology max attractiveness* exclusively determine red cluster memberships. The dense green line following it is quite small and many of the remaining green cases are left scattered across the figure. The small concentration of green cases does show that the interaction between these two parameters have certain effects on the desirability of the output (low-high means desirable outcomes, gradually declining towards high-low), but only the red cluster is clearly separated from cases with other cluster memberships. Concerning the predictive value for cluster memberships of blue and green clusters, the scatter plots in [4,1], [4,2], and [4,3] all show a clear division between blue and green cluster memberships: every plot shows a rather tight gradient from blue to green when viewing high to low. Combined with the individual effects of the parameters, the following rules can be induced:

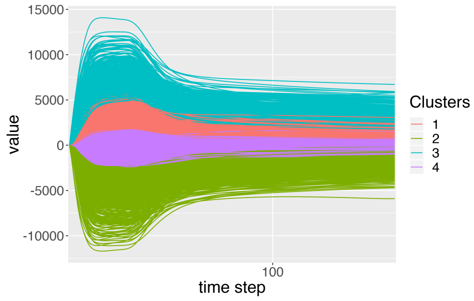
- Red cluster membership is exclusively present at an *alternative technology period* before 2010 and an *alternative max attractiveness* higher than or equal to 5.
- BEV development speed is predominantly responsible for distinguishing green and blue cluster membership: a high value most likely results in blue cluster membership, a low value most likely results in a green cluster membership.

Adding to the conclusions drawn from the sensitivity analysis, behaviour based analysis also shows that the development of the BEV sales share is solely determined by vehicle development factors. More specific, the most important differences are only found when there is a breakthrough in alternative vehicle technology development. These factors lie outside the influential boundaries of the problem owner of this research and are highly uncertain, which implies that the BEV sales share development is independent of any implemented strategy.

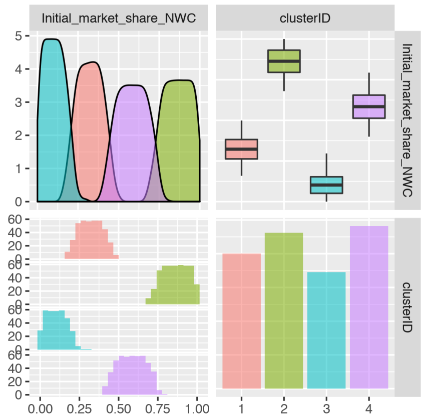
Figure 6.8 shows the CAPEX gap outcomes. The partitioning by the clustering procedures highlight the differences in behaviour, which in this case appears to be rather straightforward: the high peak in the short-term is accompanied by high values on the long term, and the same counts for low values. This implies less complexity in behaviour, which suggests that time series clustering does not necessarily provide additional insights to the sensitivity analysis. In the complete pairs plot, cluster memberships were uniformly distributed over all parameter values accept for a very clear predictor: *initial market share.*

Figure 5.11.a shows clustered ensembles that can be classified again:

1. Red: Small positive bump of CAPEX gap values on the short-term, followed by settling at moderately positive values.



(a) Clustered line plot



(b) Pairs plot

Figure 6.8: CAPEX gap filtered findings through time series clustering at no policy. CID-clustered at $k = 4$.

2. Green: Large negative dip of CAPEX gap values on the short-term, followed by settling at negative values.

3. Aquamarine: Large positive bump of CAPEX gap values on the short-term, followed by settling at positive values.

4. Purple: Small negative bump of CAPEX gap values on the short-term, followed by settling at moderately negative values.

As for desirability, the CAPEX gap should be as close to 0 as possible, indicating equal opportunities for both market party classes. When then preferring either positive or negative values, in this case a negative value is moderately preferred, for this means that the commercial parties will have positive opportunities on the market. The clusters can therefore be ranked as such: purple, red, green, aquamarine.

As seen in figure 6.8.b, the clusters are clearly divided across values of the initial market share. Apparently, initial market shares dominate the course of the CAPEX values. Cell [1,1] shows that when the *initial market share NWC* is higher, it creates lower CAPEX gap values overall (green cluster, followed consecutively by purple, red, and aquamarine). This completely agrees with former findings at the sensitivity analysis and does not provide new insights concerning the behaviour of the CAPEX gap outcomes.

Figure 6.9 shows the EVCS price per kWh clustered line plot and the corresponding pairs plot with the most important predictors.

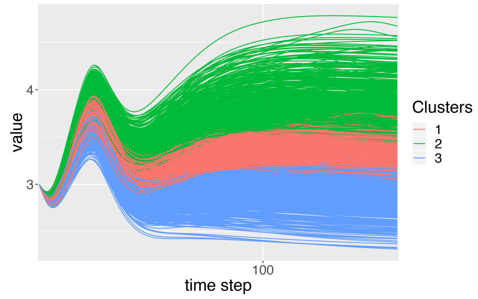
First, clusters will be classified again:

1. Red: Moderate increase followed by a moderate decrease, balancing on the lon-term at moderately high values.

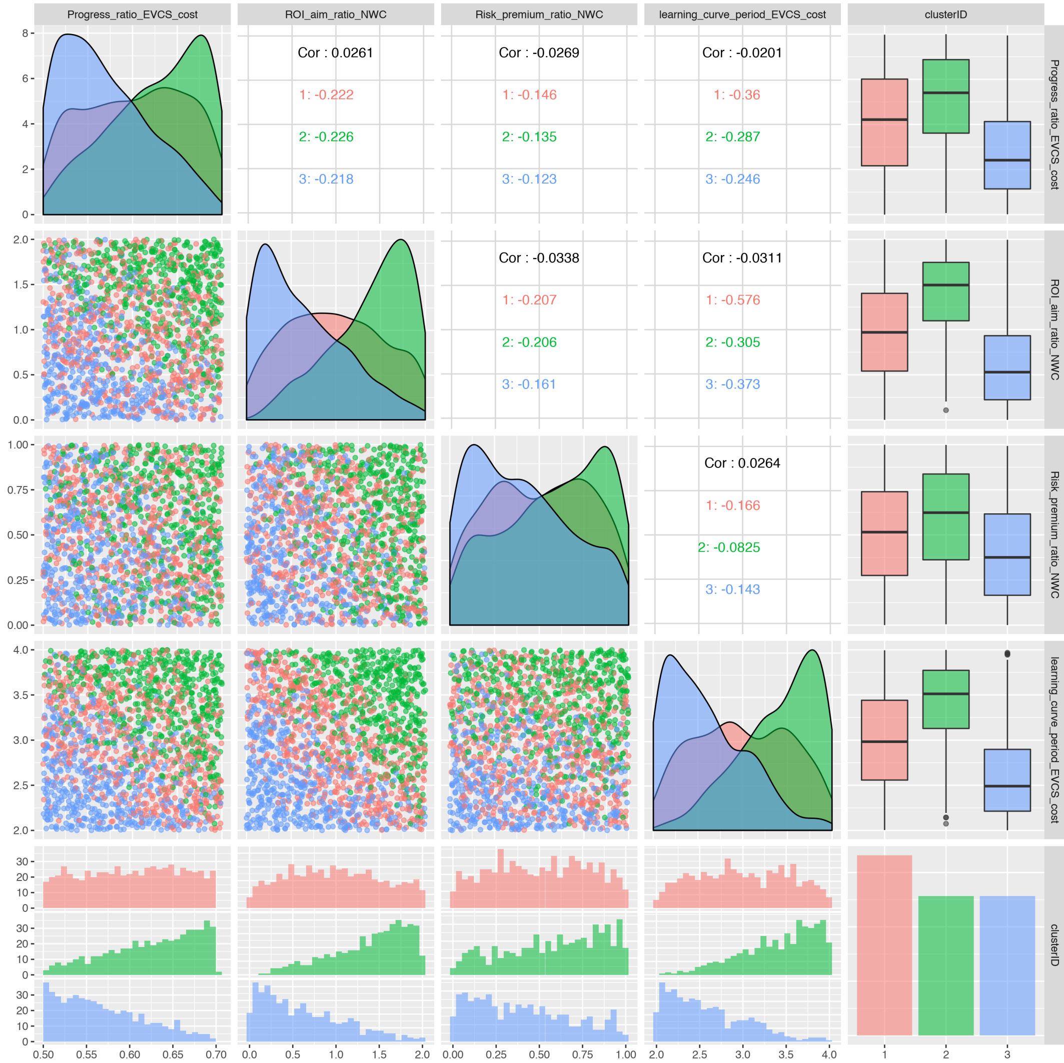
2. Green: Rapid increase followed by a moderate decrease, followed by a moderate increase again finding an equilibrium very late at very high values.

3. Blue: Slow increase fllowed by a rapid decrease, slowly descending continuously on the long-term.

A low EVCS price is unconditionally the most desired output and thus the blue cluster is the most desirable outcome ensemble, followed consecutively by red and green. The red cluster (1) is the largest, shown in cell [5,5]. The histograms at the bottom of the page all show a rather uniform distribution along all parameters, with some low case densities at all parameters' extreme values accept for the *progress ratio EVCS cost*. The green and blue cluster however are all clearly distributed by the green cluster at high values for all parameters, and blue cluster membership for the cases with low values. The peaks on the diagonal cells indicate this clearly, while still significant overlap is found for all parameters. The reasons for the overlap is clearly visible when looking at the input pairings. All show similar interactions: together the 4 parameters create



(a) Clustered line plot



(a) Pairs plot

Figure 6.9: EVCS price per kWh filtered findings through time series clustering at no policy. CID-clustered at $k = 3$.

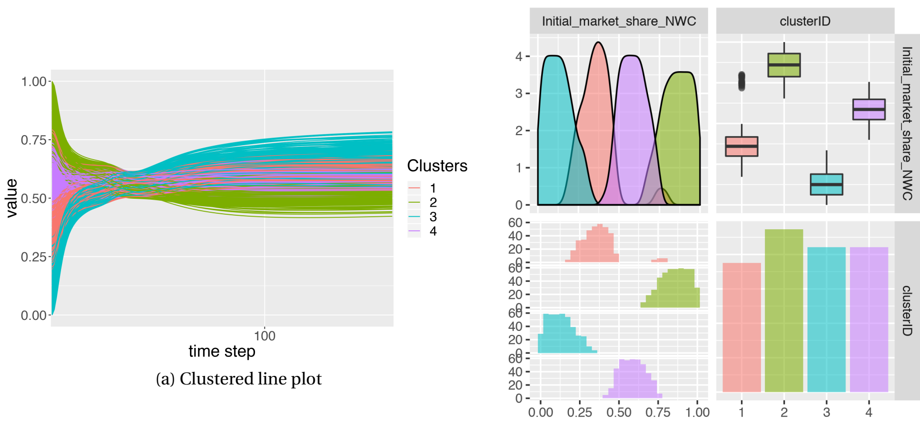
high prices when all parameters are high (green cluster). Investment behaviour parameters of a NWC (with only the investment boost excluded) have a clear effect on the price development of the market. Cell [3,3] shows the interaction of the ROI aim ratio and the risk premium ratio of the NWC to have a decent effect on the price: when both ratios are low, the most desirable outcome is realised, gradually becoming less desirable when either parameter value is increased. The learning curve parameter effects indicate the importance of the economies of scale effect: the slower the structure works, the higher the prices will remain. This effect is additionally strong enough for the beneficial effects of an active NWC on the market with different investment behaviour to be canceled out when the learning curve parameter values are low. Either cells [2,1] and [3,1] or cells [4,2] and [4,3] indicate the interactions between the investment behaviour parameters and the economies of scale parameters: the ROI aim ratio interacts significantly with the economies of scale parameters, creating an even distribution over the diagonal. However, the risk premium ratio is mostly dominated by the economies of scale parameters: the different cluster memberships mainly follow the axis of the learning curve period or progress ratio.

Even though the effects are very clear, the red cluster's cases which represents all moderate outcomes overlap significantly in all pairings. This highlights the importance of the interactions between the inputs and this means we have to be careful with drawing conclusions for single parameters. The following rules can be induced for the EVCS price results:

- The combination of low values for both cost reduction learning curve parameters excludes increasing EVCS prices on the long-term.
- Larger differences in ROI aim and risk premiums for NWC exclude increasing EVCS prices on the long-term.
- Economies of scales and investment behaviour differences reinforce each other's effects and exclusively influence the EVCS price development.

The results imply a desirability for active network companies on the market with different behaviour than commercial parties. However, the success of these activities are interdependent to the market being susceptible to cost reduction learning curves, or economies of scale. This last interaction increases the complexity of defining certain strategies to support price development through role demarcation policy because market characteristics such as economies of scale parameters are uncertain beforehand.

The cluster memberships of the market shares are solely the consequence of the *initial market rate NWC* value. When addressing figure 6.10.a carefully, it becomes clear that at the mid-section of the complete ensemble trajectory on the long term, of all clusters a significant number of cases overlap. Only the aquamarine and green clusters seems to differ on the long term. The cluster membership is therefore mainly the result of partitioning the initial values into 4 sections. The only observed effect is that high initial market shares result in lower long-term outcomes and vice versa. .



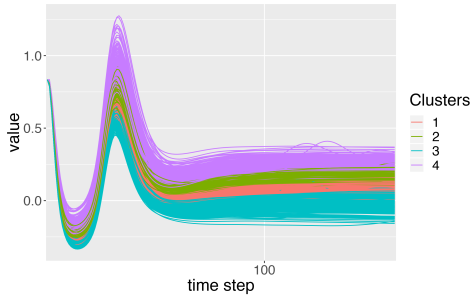
(a) Clustered line plot

(b) Pairs plot

Figure 6.10: Market share NWC filtered findings through time series clustering at no policy. CID-clustered at $k = 3$.

Figure 6.11 shows the final KPI: the ROI of commercial parties. The input parameters that influence cluster membership the most are shown in the pairs plot again. First, figure 6.11.a will be used for creating cluster narratives. An initial evaluation of the figure gives us the general behaviour: a rapid descend followed by consecutively a rapid ascend, descend and reaching equilibria. The clusters can be distinguished as follows:

1. Red: The lower mid-values belong to this cluster. Some overlap is found but especially in the peak, little variance is found.



(a) Clustered line plot

(b) Pairs plot

Figure 6.11: ROI commercial filtered findings through time series clustering at no policy. CID-clustered at $k = 3$.

2. Green: The higher mid-values belong to this cluster. Some overlap is found again and little more variance is found than in the red cluster, especially in the peak.

3. Aquamarine: The lowest values belong to this cluster. All cases with negative equilibria on the long-term are part of this cluster.

4. Purple: The highest values belong to this cluster, with a large spread of the different case outcomes.

Ranking these clusters is in this case quite easy, for the ROI commercial values represent the attractiveness for commercial parties to enter the market. The only absolutely undesired cluster is the aquamarine cluster which contains all negative long-term outcomes and descends furthest and ascends the least on the short-term. The most desired outcomes are those part of the purple cluster, followed by respectively the green and the red cluster.

Figure 6.11.b shows some very interesting results. The investment behaviour differences show to have significant influence on cluster assignments especially when pairing higher and lower valued clusters with each other or when contrasting clusters (aquamarine and purple, red and green) are separately compared. Especially the purple and the aquamarine clusters are clearly separated by the ROI aim ratio and risk premium ratio value ranges: high values excluse aquamarine cluster membership and low values exclude purple cluster membership. The green and the blue show similar, but mitigated results. Box plots in cells [1,5], [2,5], and [3,5] show the significant differences in aquamarine and purple clus, but only moderate differences can be stated for red and green clusters (the ROI aim ratio box-plots have their means not overlapping with the other box, but the boxes themselves do overlap). The pairings in cells [2,1], [3,1], and [3,2] illustrate the added interaction effects of the risk premium ratio and ROI aim ratio combined.

When interpreting these results for the ROI commercial, a trade-off concerning desirability can be found when compared with the EVCS price: higher values of risk premium and ROI aim ratios result in higher ROI values for commercial parties: blue cluster membership is due to highest values, followed by green, red, and finally purple, which is reinforced by interaction effects with each other and with the initial market share. Also the learning curve plays a moderate role, but strong statements cannot be made based on this figure. The following rules can be induced for the ROI commercial:

- Low values for either ROI aim ratio NWC, risk premium ratio NWC exclude the maximum ROI commercial values over the entire period.
- High values for either ROI aim ratio NWC, risk premium ratio NWC exclude the minimum ROI commercial values over the entire period.

Conclusively, the development of the returns of commercial parties is negatively influenced by the activities of network company when profit targets and risk valuations are very different. Lowering these differences creates better profitability for commercial parties over the entire market development period, implying that excluding network companies from the market would ensure maximum market attractiveness for commercial parties.

6.4.3. Behaviour based scenario discovery conclusions

Behaviour based scenario discovery has pointed out what factors and interactions mainly influence development curves of the outcomes of interest. By means of time series clustering, the most important predictors for different sets of outcome ensembles with coherent behaviour are identified. Further classification of these outcome ensembles creates insights on how these predictors are responsible for disrupting or stimulating the EV charging infrastructure market development. Final conclusions of these analyses are presented here.

BEV sales share development is only influenced vehicle development parameters. More specific, only a true breakthrough of a non-electricity based alternative vehicle technology can significantly influence the behaviour. The remaining scenarios are quite robust and all result in strong increasing BEV sales rates.

Cost advantages development is completely dependent of initial market shares: at high initial market shares of network companies, commercial parties have larger cost advantages over the network companies and vice versa. While equal opportunities is preferred and balanced initial market shares are most desired, this tells us that investments in extremely early stages by network companies actually are beneficial for commercial parties. The initial market shares represent the market shares that have settled before the simulated period where the first 400 charging stations have already been built or proposed. This actually shows that development on a far smaller time-scale in the very early stages of the market development has a significant effect on later development of cost advantages.

Lower EVCS prices per kWh are realised when investment behaviour differences are high: when network companies determine very low risks and aim for low profits, prices are lowest throughout the entire simulated period. Additionally, learning curve effects have a similar influence: the stronger learning curve structures are present, the lower the charging fees become. The importance of these dynamics is highlighted by the fact that price variations increase towards the end of the simulation. A large variation is still present within clustered outcome ensembles but overall effects show that investment behaviour differences and learning curve effects positively influence the price outcomes. From the consumer's perspective the activities of network companies are beneficial and these effects are amplified when economies of scale are applicable on the market.

The partitioning of the market share outcomes by behaviour has shown to be completely based on initial values, whereas long-term values of the different clusters overlap considerably. Thus, no additional insights on market power distributions are provided by behaviour based scenario discovery.

The behaviour of the estimated return of commercial parties is concluded to be mainly influenced by activities of network companies when profit targets and risk valuations are very different: larger differences create less profitability for commercial parties over the entire market development period. When network companies would not be active on the market, the market attractiveness for commercial parties would be ensured.

A clear trade-off is observed: active network companies on the market with different investment behaviour results in positive price development, but negative ROI development for commercial parties. Lower prices indicate a more efficient supply chain and thereby a more developed market, but negative ROI development means a decreasing attractiveness of the market for commercial parties. Incumbents are increasingly powerful on the market and unequal competition will increase. The effects of investment behaviour differences are heavily amplified by learning curve effects, however these effects result in greater value differences on price development than on the profitability.

6.5. Base case analysis conclusions

In this chapter the outcomes of the modelled system are analysed when no policy is implemented. The model outcomes have been explored for initial observation and to verify and validate the model outcomes. Subsequently the model outcomes' sensitivities to the identified uncertainties have been analysed by calculating Sobol indices, and the behaviour of the model has been analysed through time series clustering. The outcomes of this chapter represent the base case and are aimed at providing a complete understanding of the base case results.

Model exploration has showed that the amount of EV charging stations per BEV is very robust to all uncertainty ranges, finding its final equilibria at the desired 25%. The EVCS rates are clear responses to BEV development and a robust balance is found after less than 10 years. The vehicle development process however develops with significant independence to other dynamics in the system: its driving factors are all part of the vehicle development structure, where the only important difference is made when a non-electricity based alternative vehicle technology breaks through on the vehicle market. The vehicle market is not influenced by the EV charging infrastructure market and the vast majority of scenarios result in steadily increasing BEV sales.

Cost advantages over time seem to be influenced solely by initial market shares of the market parties. These effects show the relevance of very early operations on the market which can not be explored by this research's time scale. The effects of cost advantages are however structurally connected to ROI estimations and market price mechanics, allowing relevant insights to be measured through these KPI's instead.

Investment behaviour differences have shown to have significant effects on final outcomes. When network companies invest by more aggressive rates, the EV charging price develops faster. When profit targets of network companies are lower, the charging price develops faster as well, but ROI estimations for commercial parties are negatively influenced and network companies will own dominant market shares. In further development of the market, risk valuation differences also support these effects and economies of scale effects amplify all mentioned influences.

The most important observation is the trade-off between profitability for commercial parties and overall price development. From a strict, aggregated and technical view, allowing network companies on the market leads towards the most positive market development results, for the price develops in the most desirable manner when low profit targets, lower risks, and more aggressive investment responsiveness is present on the market. However, these scenarios disrupt the freedom on the market by raising entrance barriers and increasing advantages for incumbents.

7

Policy Analysis

7.1. Experimental setup

The following settings have been used to represent the no policy base case. Info and references about the initial values of these variables can be found respectively in Chapter 4 and Appendix B. First, the uncertainties are briefly presented.

Uncertainties

- Alternative technology introduction year (Range: 2000-2030)
- Alternative vehicle technology max attractiveness (Range: 0-8)
- Alternative vehicle development speed (Range: 0,05-0,35)
- BEV development speed (Range: 0,1-0,2)
- Risk premium ratio NWC (Range: 0-1)
- ICE average fuel price (Range: 0,80-1,60)
- ROI aim ratio NWC (Range: 0-2)
- NWC public incentive investment boost (Range: 0-1)
- Initial market share NWC (Range: 0-1)
- learning curve period EVCS cost (Range: 2-4)
- learning curve period charging speed (Range: 2-4)
- Progress ratio EVCS cost (Range: 0,5-0,7)
- Progress ratio EVCS charging speed (Range: 0,3-0,5)

Policy impacts will be analysed in 2 different implementations. The "defined policies" implementation is done by independently specifying each policy in a different model, which will each be simulated over the entire outcome space by running the same 1000 scenarios as with no policy. The different specified policies will then be tested in comparison to each other. The following policies have been modelled:

Defined policies

- No policy: No policy implemented. Base case (Chapter 5).
- No market entry: The NWC is not allowed to enter the market at all.
- 5 years activity period: Temporary market entrance is allowed for 5 years.
- Market share cap 50%: The maximum market share allowed for NWC is 50%.
- Shareholder activation: Stimulating shareholders to demand regular dividend payments and more transparency. Increasing stakeholder involvement moves NWC risk perceptions to a value similar to the commercial value.

The second implementation enables the possibility to mix policies. This is done by defining all policies as levers, which will be sampled through latin hypercube sampling as was done with the uncertainties. The levers are a flexible implementation of the defined policies, however when the no entry policy is active it structurally disables other policy levers for it disables investments by network companies altogether.

Policy levers

- No entry switch: Binary switch, 0 is off, 1 is on.
- Market entry period: The amount of years from the initial time that the NWC is allowed to be active on the market in years. Ranges from 0-10 years (2010-2020)
- Market share cap: The maximum market share for a NWC to have, Ranges from 0-1, where 1 is 100% market share.
- Shareholder activation switch: Binary switch, 0 is off, 1 is on.

As concluded from Chapters 3 and 4, the most important metrics of interest are the market price for EV charging, capital expenditures, ROI's of commercial market parties, EV sales rates, market shares, and the amount of charging stations per BEV. For exploratory reasons, the actual BEV shares in the vehicle mix are included throughout the exploratory phase. The following key performance indicators are registered as followed, with corresponding unit definitions:

Key Performance Indicators

- BEV sales share: Registered as a ratio from 0-1, where 1 represents 100% BEV's in the vehicle mix.
- EVCS per BEV: Registered as a ratio from 0-1, where 1 represents a coverage of 1 EVCS per 1 BEV.
- CAPEX gap: Registered in €, where the number represents the difference in CAPEX for commercial parties compared to NWC. A positive number is a higher CAPEX for commercial parties than NWC, and vice versa.
- EVCS price per kWh: Registered in €/kWh, representing the charging fees.
- Market share NWC" Registered as a ratio from 0-1, where 1 represents a 100% market share of NWC.
- ROI Commercial: Registered as a ratio value without boundaries, where 0 represents the break-even point and 1 represents 100% returns expected to be realised by commercial parties on a new EVCS project.

All outcomes are captured as full time series outcomes over a period of 20 years (2010 - 2030). The parameter values of the experiments are again sampled using LHS. The base number of 1000 scenarios is used again here. With exactly 5 different defined policy scenarios this implies $5 \times 1000 = 5000$ experiments for the defined policies sampling. For the policy levers, 10 different policy combinations are sampled, resulting in $10 \times 1000 = 10000$ experiments for mixed policies sampling. These sets of outcomes will also be used for time series clustering.

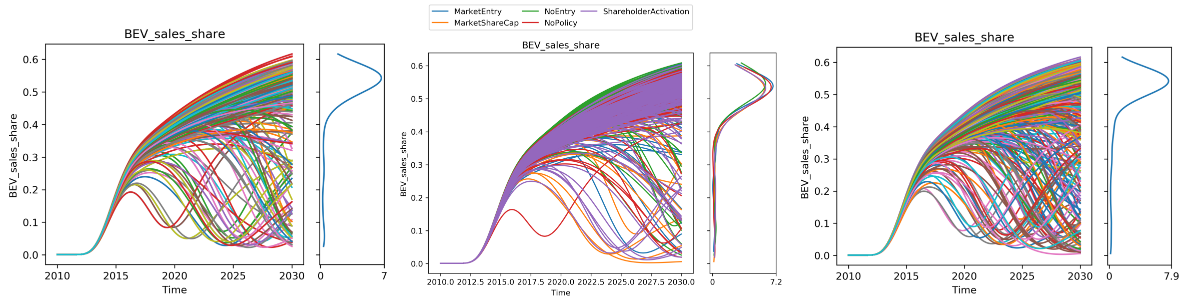
For the Sobol sensitivity analysis, a specific Sobol sampling method is used. The mixed policy Sobol tests will be used for both concepts, for interactions of all policy options will be highlighted there. The Sobol technique requires a larger amount of experiments, determined by taking the original set of scenarios n, and increasing it relative to the amount of predictors p into $N = n(2p+2)$ samples. The policy levers will be sampled as uncertainties in the sampler, adding the number of levers to the number of predictors p to 17 instead of 13. This implies running $1000 \times (2 \times 17 + 2) = 36000$ scenarios.

7.2. Policies validation and exploration

First, the initial outcomes will be explored again. This will be done by generating line-plots with density plots of all outcome cases for both defined and mixed policies. Different than during base case analysis, the three different datasets (no policy, defined policies, and mixed policies) will be shown together to allow comparison. The goal is to generate a general idea of the performance of the entire ensembles of either defined policies or mixed policies compared to the no policy base case. Defined policies are additionally coloured by policy to highlight the individual effects of each policy on the performance indicators. Figure 7.1 shows the outcome sets for BEV sales share.

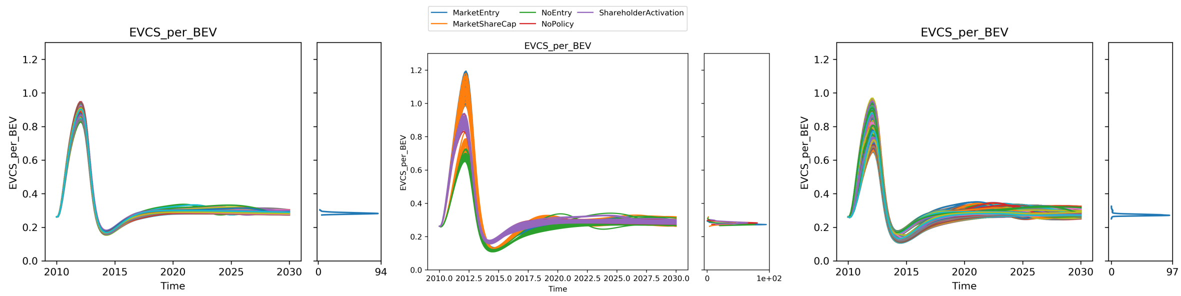
The BEV sales share shows no observable influences by implemented policies on the overall outcome space. These impressions are in line with the conclusions of the base case analysis (Chapter 6), for the BEV sales share showed not to be influenced by input parameters other than the uncertainties that are a direct part of the vehicle development structure. All policies are role demarcation policies, which solely influence market party behaviour, thus no considerable impact would be expected.

The EVCS per BEV are however slightly influenced by the policy implementations, as can be seen in figure 7.2. The Defined policies plot shows no impact at all by shareholder activation, but all other policies clearly



(a) No policy (b) Defined policies (c) Mixed policies

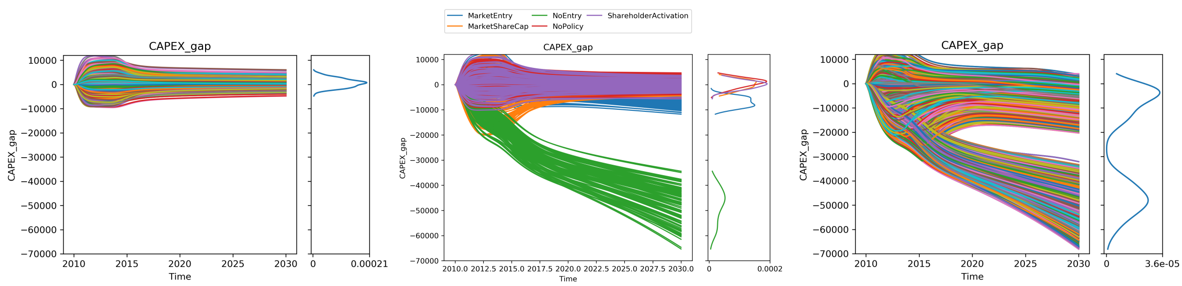
Figure 7.1: Lineplots of the complete outcome space of BEV sales shares at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).



(a) No policy (b) Defined policies (c) Mixed policies

Figure 7.2: Lineplots of the complete outcome space of EVCS per BEV at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

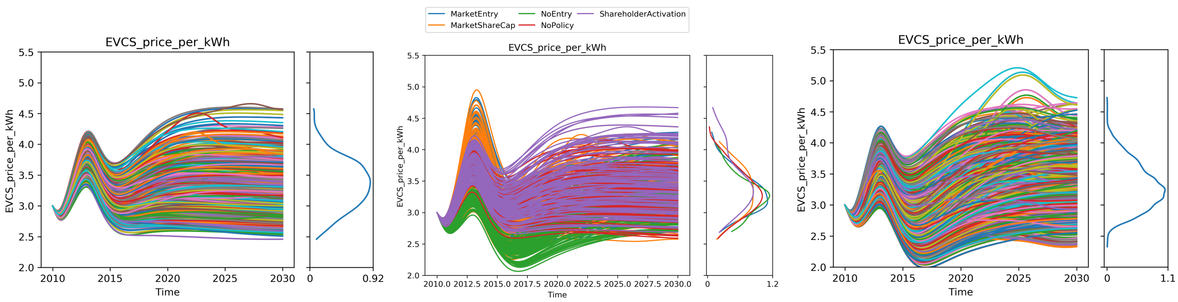
influence the peak at 2012. The height of the peak varies from a minimum around 0.62 due to the no entry policy implementation, up to a maximum of 1.2 caused by the allowing the temporary market entrance of network companies or by implementing a market share cap, of which the latter causes a large variance as well. After 2015 however, no differences in behaviour or outcomes can be observed. When considering the meaning of these values, the influences on the peak at 2012 are not necessarily of significant interest: The ideal value of EVCS per BEV is in the model assumed at 0.25, meaning that any higher value suffices from a consumer point of view, but lower values show underdevelopment of the market. The lower values at 2015 are not very much influenced by the policies, as is also shown in the mixed policies graph. Additionally, the density plots show an almost exact same sharp peak at 0.25. Focusing on the most relevant insights of the EVCS per BEV outcomes, the outcomes are considered to be robust to policy implementations.



(a) No policy (b) Defined policies (c) Mixed policies

Figure 7.3: Lineplots of the complete outcome space of CAPEX gaps at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

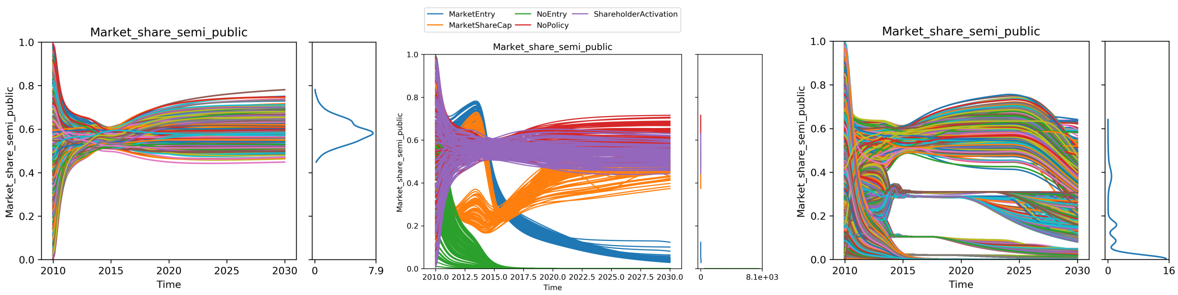
Figure 7.3 shows the impacts of the different policy implementations on the CAPEX difference between commercial parties and network companies. Figures 7.3.a and 6.3.b show a very clear difference as an entire ensemble of outcomes descends continuously towards the end. The defined policies plot however shows that the entire ensemble is the result of the no entry policy. This is no surprise since economies of scale will increase the differences continuously, resulting in an increasingly large difference in costs between the two parties. Another difference can be seen in the density plot of figure 7.3.b: the temporary market entry policy (shown in blue) results in lower values than other outcomes with practically all its values below 0. Although the smaller difference initially appears to indicate unique behaviour, these outcomes are essentially a combination between the no policy and the no entry policies: the system does not change for the first 5 years, but then the CAPEX gap will continuously decrease because of the absence of the network company on the market. Other policies that may have less obvious explanations appear to only slightly influence the development. The mixed policies graph also shows no distinctive behaviour when compared to the defined policies, accept for the declining trend at the final period and seen from the density plot: on the long-term the cost advantages for network companies are eliminated for almost the entire outcome ensemble.



(a) No policy (b) Defined policies (c) Mixed policies

Figure 7.4: Lineplots of the complete outcome space of EVCS charging fees at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

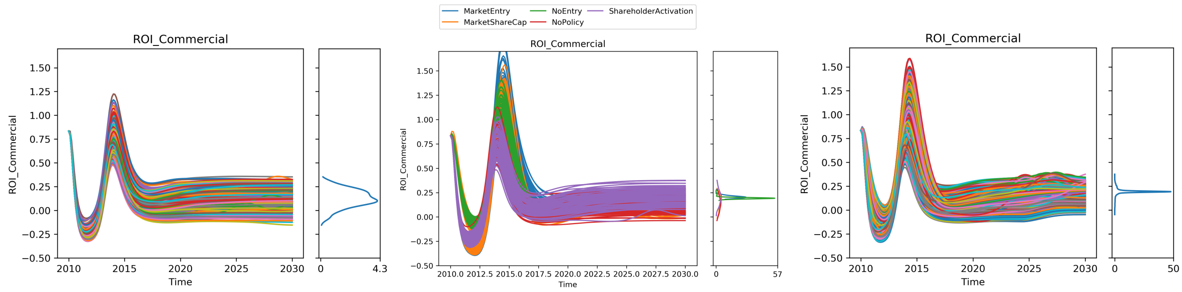
The EVCS price per kWh for different policies shown in figure 7.4 does appear to be changed significantly. When policies are implemented, higher prices are realised and more price increases are found after the minima at 2017. Another interesting observation is the fact that on the short-term, the policies market entry period and market share cap create significantly higher peak prices, where on the long-term the mixed policies have some considerably higher prices. The lower prices are present when a network company is not present on the market at all (no entry policy shown in green), however these value seem to rise more rapidly towards the end. Shareholder activation individually again shows no large differences in behaviour when compared to no policy. The mixed policies additionally do not seem to change the height of the peak in 2013, but the ensemble has an increased spread on the long-term: lower values at 2017, but also higher values in 2025. When density plots are compared it is however seen that the peak has sharpened and lowered: the outcome cases are more concentrated around the mean, which is slightly lower as well.



(a) No policy (b) Defined policies (c) Mixed policies

Figure 7.5: Lineplots of the complete outcome space of network company market shares at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

The market shares show a lot of differences in behaviour. However, most policies directly influence market share through the investment rate modification, which makes this behaviour predictable. The different effects of specific policies are clearly shown by figure 7.5.b. The slow descends of the no entry and market entry period policies is the result of the model just stopping further development of EVCS for network companies, which results in a slow deterioration of the market share based on the lifetime of EVCS (12 years). The shareholder activation policy is however the only policy implementation that is part of a different structure in the model than the investment behaviour and its results therefore provide more relevant insights. The implementation of shareholder activation seems to increase the robustness of the outcomes in a positive manner: it narrows down the market share variation, while moving the mean strongly towards 0.5. A market share of 50% means that network companies and commercial parties are equally active on the market, which indicates an even distribution of market power. Since the different parties are modelled as a duopoly of two market party classes, this is theoretically the ideal result. The complex behaviour of the market share outcomes for mixed policies is due to lever sampling: the lines dropping at various moments in time are an obvious result of the market entry period being sampled, and different heights are the obvious result of the market share cap being varied. Since various policy options are mainly aimed at manipulating market shares, the main interest lies in finding out what differences in market shares do with the market development and therefore the market shares will not be included in further analysis.



(a) No policy (b) Defined policies (c) Mixed policies

Figure 7.6: Lineplots of the complete outcome space of expected ROI's of commercial parties at no policy, defined policies and mixed policies. The density plot to the right of each graph illustrated the distribution of case outcomes over the y-axis. Total runtime is 20 years (2010 - 2030).

Figure 7.6 shows rather interesting results. The ROI commercial outcomes as a whole have an increased spread as a result of the policy implementations: the peak for the defined policies has increased to 2.0 due to market entry period, and mixed policies result in an increase to 1.5, where the no policy peak was found at 1.2. The long-term effects however are more robust: while the upper and lower boundaries are at similar levels, the density plot shows an extremely large concentration of cases around 0.25 for defined and mixed policy outcome ensembles. This value is not only higher than the 0.2 mean at no policy, but it is also more robust considering the concentration. The density plot in figure 7.6.b shows that the increase in value and robustness are due to the no entry and the market entry period policies, while other policies only slightly increase the value. Especially no entry seems to result in an almost certain ROI of 0.25 on the long term. This means that overall the effect of policies on the ROI commercial is positive since it creates higher estimated returns for commercial parties, making EVCS development a considerably more attractive business case.

Concluded from the exploration phase is primarily the seeming insensitivity of BEV sales shares and EVCS per BEV to the implementation of policies, of which the last is also highly robust. Second, CAPEX gap and market shares are found to show only predictable behaviour differences due to policy implementations. Policies have shown significant impacts on the development of the EVCS price and the ROI of commercial parties. EVCS price per kWh is varied in questionable manner by the policies: positive effects on the short-term behaviour are generally complemented by negative effects on the long-term behaviour. The ROI of commercial parties is most significantly influenced by the no entry policy: long-term values all end up at almost 0.25. This is directly followed by the market entry period policy that results considerably robust and slightly higher values. Other policies increase the average ROI on the long-term but remain similar robustness as no policy.

7.3. Sensitivity analysis

For the sensitivity analysis of the policies, the mixed policy model will be used for a single complete assessment of the policy and uncertainty interactions. In order for the sensitivity analysis to be meaningful, the outcomes are reviewed to be unimodal and symmetrical. The density plots in the previous section show bi- and multimodality for the CAPEX gap and the market shares. Since market shares are manipulated directly by the policy implementations it is not necessary to evaluate this outcome comprehensively. The CAPEX gap however is an interesting outcome, but the strong bimodal density plot indicates that results of the sensitivity analysis will not be sufficiently usable. The CAPEX gap will be examined further during behaviour based scenario discovery.

7.3.1. Sobol indices

For each outcome variable, the $S1$ and ST of every uncertainty on that outcome variable shall be shown for both the short- (2010-2020) and the long-term (2030) again. A high $S1$ means the direct effect of a certain uncertainty on the corresponding performance indicator is high, and when total effect ST is significantly higher this means that interaction effects are significantly dominant. Regarding sensitivity to certain policies, it is important to consider that the sensitivity is a result of outcome variance changing strongly as a result of a change in the input parameter's value. This means that the indices will show how strong the impact is of the entire input range of a parameter on the outcomes. Switches such as been used for the no entry and the shareholder activation therefore generally show little impact through the Sobol analysis, which is considered acceptable since these switches are significantly more accurately addressed during the exploration phase and time series clustering. The effects of these switches will therefore be neglected and the focus of the sensitivity analysis will lie on real parameters: market entry period, market share cap, uncertainties, and their interaction effects. Detailed plots for specific relevant moments in time can be found in Appendix D.1 as well as second order effect calculations for outcomes where significant interaction effects are observed.

	EVCS price per kWh		BEV sales share		ROI Commercial	
	ST	S1	ST	S1	ST	S1
Alternative technology introduction year	0,0003	0,0006	0,2640	0,1649	0,0007	0,0003
Alternative vehicle development speed	0,0002	0,0006	0,0426	0,0054	0,0006	0,0001
Alternative vehicle technology max attractiveness	0,0003	0,0003	0,2245	0,0498	0,0007	0,0002
BEV development speed	0,0002	0,0005	0,1458	0,1418	0,0006	0,0000
ICE average fuel price	0,0001	0,0001	0,4506	0,4553	0,0000	0,0003
Initial market share NWC	0,0923	0,0678	0,0027	0,0008	0,1893	0,1176
Market entry period	0,0000	0,0001	0,0000	0,0000	0,0000	0,0001
Market share cap	0,5822	0,5513	0,0025	0,0007	0,5678	0,4611
NWC public incentive investment boost	0,0057	0,0032	0,0007	0,0004	0,0105	0,0043
No entry switch	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Progress ratio EVCS charging speed	0,0002	0,0004	0,0008	0,0003	0,0006	0,0001
Progress ratio EVCS cost	0,0358	0,0316	0,0000	0,0000	0,0433	0,0409
ROI aim ratio NWC	0,2060	0,1892	0,0011	0,0005	0,1107	0,0824
Risk premium ratio NWC	0,0337	0,0288	0,0010	0,0007	0,0852	0,0690
Shareholder activation switch	0,0000	0,0001	0,0000	0,0000	0,0000	0,0001
learning curve period EVCS cost	0,0936	0,0925	0,0000	0,0000	0,1080	0,1019
learning curve period charging speed	0,0002	0,0004	0,0012	0,0009	0,0006	0,0001

Figure 7.7: Sobol indices for all relevant outcomes on the short-term. Values are shown by outcome variables (columns), Sobol index (subcolumns), and uncertainties (rows). Short-term refers to combined index outcomes from 2010-2020. Colours highlight the effects of the variables: higher values are darker and cells become purple when more significant (starts from above 0.10).

Figure 7.7 shows that the EVCS price per kWh is influenced by several uncertainties combined but the largest effect is again found with the profit target differences (ROI aim ratio). The effect of the profit difference variations on the variance of the price does show to be mitigated by policy implementations when compared to short-term sensitivity results during the base case analysis (Figure 6.2). The scores here show a clear reason for this: the variance is predominantly accounted for by variations on the market share cap policy lever. Determining the market share cap therefore shows to be a highly efficient instrument to influence price development on the short-term. This also means on a higher level of aggregation that the market power and participation of a network company strongly influences short-term price development. The market entry period shows no impact on short term price development at all.

The BEV sales share is evaluated again to see whether policies may still have some effect on the vehicle development outcomes. Comparing Figure 7.8 with the base case outcomes at Figure 6.2 indicates clear and verified conclusion: index scores are not significantly changed and no considerable effect is added by policy levers, meaning that the BEV sales share is indeed not sensitive towards policy implementations. Long-term effects will be evaluated briefly to support this conclusion.

Finally, the estimated returns of commercial parties on the short-term can be examined. Again, variations on market share cap settings appear to have very strong effects on the outcome. Other effects are mitigated slightly, but total effects on the estimated ROI of commercial parties are again distributed quite similar to base case analysis results. An interesting addition however is the non proportional mitigating effect the application of a market share cap has on the main effect of the initial market share. As supported by reviewing second order effects, the market share cap has very strong interaction effects with the initial market share uncertainty (Appendix D.1). The returns for commercial companies therefore shows to be predominantly sensitive to the specific combined settings of initial market shares and the market share cap value.

Overall the market share cap is the only variable policy lever that significantly affects relevant short-term market development metrics. The market entry period has no short-term effect at all even though the period is set at multiple values between 0 and 10 years, meaning that even at very short market entry periods any effect is not there within at least 5 years after network company market activity restriction. The market share cap however seems to successfully mitigate short-term influences by uncertainties and its dominant effects suggest it to be a very useful tool to influence short-term market development.

	EVCS price per kWh		BEV sales share		ROI Commercial	
	ST	S1	ST	S1	ST	S1
Alternative technology introduction year	0,0232	0,0032	0,6804	0,2165	0,0493	0,0029
Alternative vehicle development speed	0,0089	0,0008	0,1632	0,0062	0,0403	0,0039
Alternative vehicle technology max attractiveness	0,0232	0,0049	0,7031	0,2885	0,0477	0,0046
BEV development speed	0,0004	0,0006	0,0437	0,0439	0,0010	0,0003
ICE average fuel price	0,0000	0,0000	0,0015	0,0017	0,0000	0,0001
Initial market share NWC	0,0152	0,0041	0,0001	0,0003	0,1450	0,0936
Market entry period	0,0254	0,0019	0,0002	0,0006	0,2082	0,0693
Market share cap	0,0331	0,0023	0,0006	0,0007	0,2176	0,0016
NWC public incentive investment boost	0,0004	0,0008	0,0000	0,0000	0,0020	0,0006
No entry switch	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Progress ratio EVCS charging speed	0,0002	0,0004	0,0001	0,0000	0,0009	0,0005
Progress ratio EVCS cost	0,2718	0,2687	0,0026	0,0032	0,0054	0,0010
ROI aim ratio NWC	0,0997	0,0768	0,0017	0,0010	0,4700	0,3162
Risk premium ratio NWC	0,0410	0,0290	0,0006	0,0005	0,2202	0,1576
Shareholder activation switch	0,0001	0,0002	0,0000	0,0000	0,0000	0,0000
learning curve period EVCS cost	0,5437	0,5314	0,0057	0,0052	0,0029	0,0035
learning curve period charging speed	0,0002	0,0004	0,0002	0,0002	0,0009	0,0005

Figure 7.8: Sobol indices for all relevant outcomes on the long-term. Values are shown by outcome variables (columns), Sobol index (subcolumns), and uncertainties (rows). Long-term refers to the end-state outcomes at 2030. Colours highlight the effects of the variables: higher values are darker and cells become purple when more significant (starts from above 0.10).

A prior verification of BEV sales share effects is seen from Figure 7.8, allowing a final conclusion concerning vehicle development: no meaningful influence of role demarcation policy is observed on vehicle development, as well as no meaningful influence found by charging infrastructure market parameter's. On the other KPI's, long-term index scores show very different results. The market share cap effects are much less on long-term performance, where especially price development on the long-term shows to be insensitive to the policy. Cost reduction learning curve effects and some added effect by profit target and risk valuation differences now predominantly account for the variance in long-term price development. For the ROI estimations of commercial parties, the market share cap still has significant interaction effects. However the main effect is practically absent and especially the market entry period seems to provide additional interaction effects. When second order effects are examined (Appendix D.1), the $S2$ scores indicate that the policies together have no interaction effects at all but the interaction with uncertainties, and predominantly with profit target differences, explain an important portion of the variance of the ROI commercial outcomes on the long-term.

Policy effects on the long-term are not very strong, but the ROI of commercial parties are considerably sensitive to the interaction effects between both the market entry period policy and the market share cap policy. The policies do no interact with each-other and their effects on price development are not considered to be significant (ST index scores below 0.05). In general the strongest sensitivity on the long-term of price development is shown to cost reduction learning curve parameters, and ROI commercial is most sensitive to profit target and risk valuation differences.

7.3.2. Sensitivity analysis conclusions

In this phase, the sensitivity analysis is performed again but with policies implemented. The results are compared with Chapter 6 results, allowing a clear understanding of the added impacts of different policy instruments on the outcome variation. Both short- and long-term outcomes are evaluated and the most relevant conclusions will be presented here, with a specific focus on policy parameters.

Verifying previous Chapter's conclusions, the BEV sales share remains sensitive solely to vehicle development parameters, with strongest influence coming from interaction effects between alternative vehicle development parameters. No policy implementations has shown to be effective in manipulating BEV sales shares.

On the short-term, the market share cap has a very dominant influence on both price and ROI development. Active market share cap policy very effectively mitigates investment behaviour effects and variance created by economies of scale variations. The policy lever alone accounts for about half of all variance in the price and ROI outcomes, where interaction effects are only responsible for considerable influence on the shot-term ROI estimations of commercial parties.

On the long-term, a more distributed effect is shown: price and ROI development are not predominantly sensitive to policy lever settings any more and second order effects are highly influential on shaping profitability for commercial parties. Profit target differences and learning curve intensity individually account for the majority of the variance created on respectfully the long-term ROI commercial outcomes and price development. The market entry period influences long-term ROI outcomes through interaction effects with investment behaviour or learning curve parameters.

The market share cap policy lever is a highly effective policy for manipulating short-term market development outcomes. The former dominance of investment behaviour and economies of scale learning curve parameters in the base case is significantly mitigated and the outcomes are very sensitive to changes in market share cap. The market entry period only has some effect on ROI commercial outcomes on the long-term, but both this effect and market share cap effects only influence the ROI outcomes through interaction effects in later development stages. Long-term outcomes remain predominantly influenced by either investment behaviour differences or economies of scale intensity. The presented policy levers can conclusively be used as effective policies when price or ROI development manipulation is desired.

7.4. Behaviour based scenario discovery

The number of KPI's for the time series clustering has been narrowed down by previous findings to EVCS price per kWh, the CAPEX gap, and the ROI Commercial. Like during base case analysis, first the silhouette widths are calculated, followed by the clustering of the complete outcome space. The silhouette width plots and corresponding reasoning for *k* value choices can be found in Appendix D.1.1 for the defined policies and in Appendix D.2.1 for the mixed policies. Because the best suitable method has been tested in the previous chapter already and to support consistency in the outcomes, CID has been used again for both the defined and mixed policy analysis. After clustering, pairs plots are generated again to review the behaviour of each parameter. The complete pairs plots are included in Appendix D.1.3 for the defined policies and in Appendix D.2.3 for the mixed policies and the most relevant findings are presented here. For referring to cells belonging to the pairs plots, index-1 notation will again be used (a cell in the given pairs plot grid will be referred to as [row,column]). First, the defined policies have been analysed in a separate section, followed by the mixed policies. Finally, the combined results are concluded in the final section.

7.4.1. Defined policies

Cluster counts are found through assessment of silhouette widths which has created the following results:

Cluster counts per outcome variable:

- CAPEX gap *k*=4
- EVCS charging price: *k*=5
- ROI Commercial: *k*=3

Due to the necessary conversion of data from the experimentation software (Python) to the software that has been used for the clustering sequence (R), the policies have been assigned numbers as a reference. The following policies correspond with the numbers:

0 - No policy

1 - No entry

2 - Market entry period of 5 years

3 - Market share cap at 50%

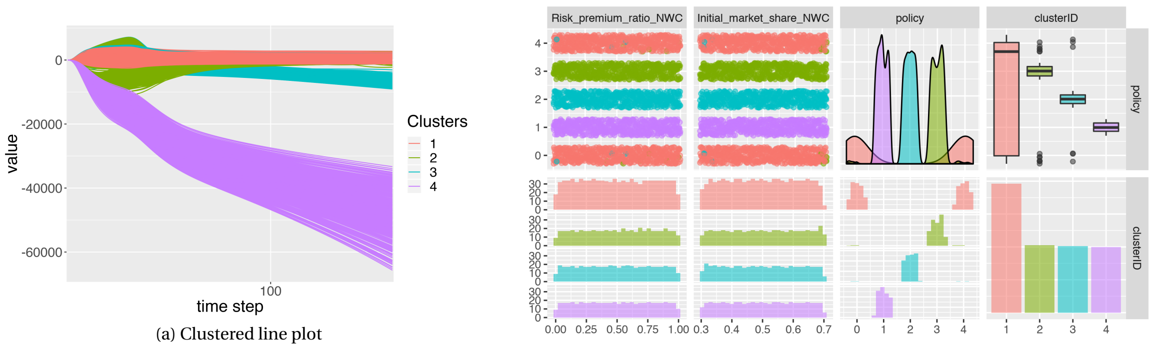
4 - Shareholder activation

The CAPEX gap will be reviewed first. An initial observation when comparing figure 7.9.a with figure 7.3.b is the remarkable similarity of both figures. From just the lines plot it can almost certainly be concluded that the CAPEX gap cluster memberships are dependent of what type of policy is active. The pairs plot shows the same thing, however a small addition is found regarding the activity of a certain policy measure when figure 7.9.b is closely examined. The red cluster is completely assigned to all cases belonging to either the no policy scenarios and the shareholder activations scenarios. Cell [2,3] verifies this specifically as the cluster memberships being completely dependent of a case's policy scenario: all cases of the red cluster belong either to no policy scenarios or shareholder activation scenarios, all purple cluster cases belong to the no entry scenario, all aquamarine cluster members are market entry period cases, and all green cases are the result of a market share cap. This means that regarding the CAPEX gap, all policy implementations accept for shareholder activation are perfectly effective in generating significantly and measurable differences in behaviour accept for the shareholder activation option. Only shareholder activation and no policy result predominantly in undesirable positive CAPEX gaps (red cluster).

The EVCS price per kWh is influenced in a more distributed manner, making figure 7.10 rather complex. First, the clustered line plot shows more actual behavioural differences. I will start by formulating the cluster narratives based on the line plot:

1. Red: The highest values of the ensemble belong to this cluster. The behaviour specifically contains a very high peak (with considerable variation regarding the height of the peak), followed by a small dip and the cases reach its equilibrium about 5 years after that..

2. Gold: The mid-range of the total ensemble: a moderate peak in the beginning, followed by an almost immediate equilibrium right after. relatively little variation in values is found between different cases.



(a) Clustered line plot

(b) Pairs plot

Figure 7.9: CAPEX gap filtered findings through time series clustering at defined policies. CID-clustered at $k = 4$.

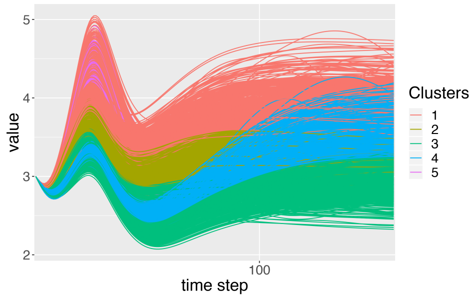
3. Green: A minor peak in the first 5 years, followed by a descend right after, consecutively followed by a small rise again which reaches its equilibrium after 2022,5 (time-step 100). There is increasing variation between cluster case values.

4. Blue: Similar to green, a minor peak followed by a descend, but blue cluster cases keep on rising after the descend.

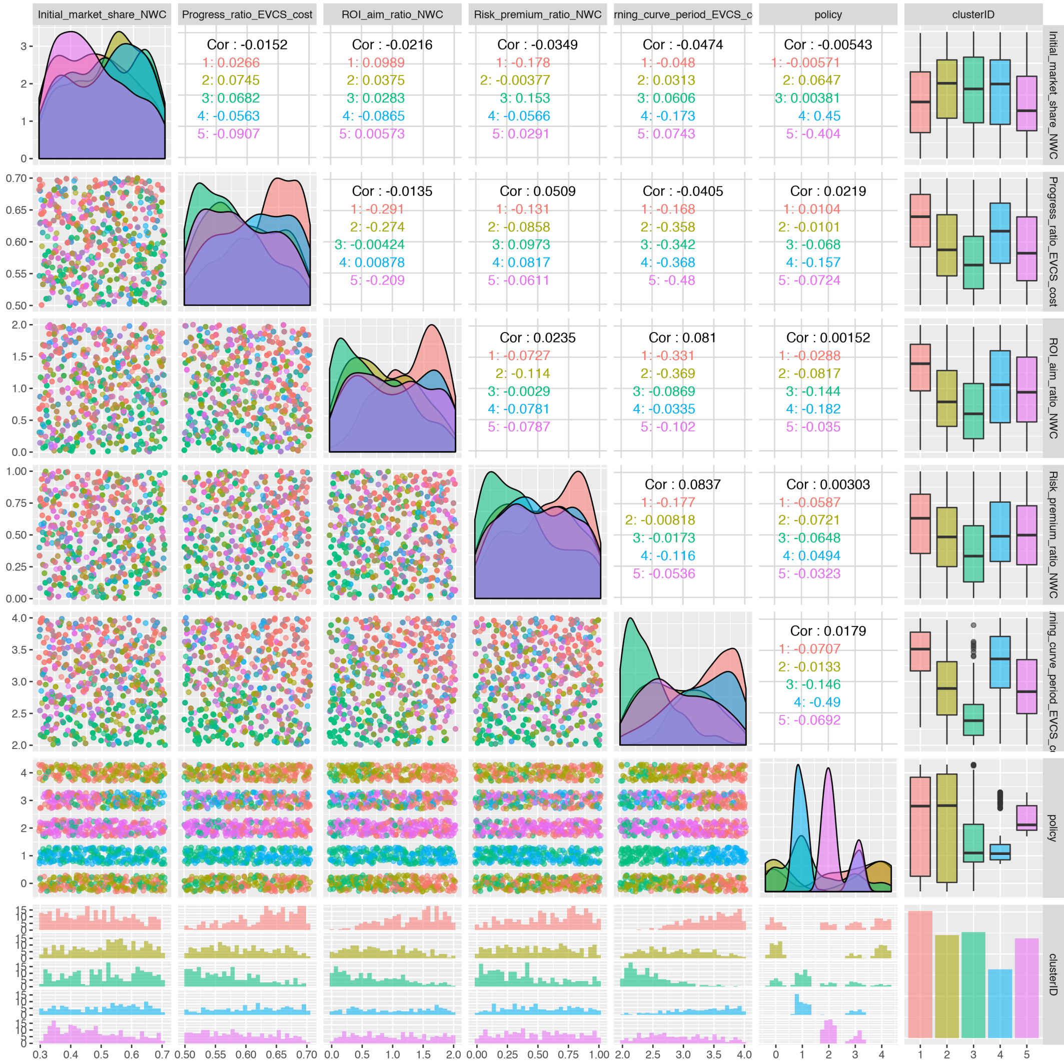
5. Purple: A very strong peak wil little variation is found in the beginning, followed by a sharp descend again and an equilibrium is found relatively fast.

The most desirable outcomes are the low values, making the green and blue clusters more desirable than others. However, both of these clusters (especially blue) show a rise on the long-term, making the scenarios belonging to this clusters mainly desirable on the short-term. Figure 7.4.b showed very clearly how all policy outcome ensembles are distributed similarly over the total outcome space, indicating that there must be at least one uncertainty co-responsible for certain cluster memberships. The complete pairs plot in the appendix showed that the total explanation is a complex combination of many uncertainties of which the most decisive parameters are shown in figure 7.10.b.

Again the shareholder activation policy seems to have little to no added influence on the cases' cluster membership when compared with the no policy option. However, when viewing cell [7,6] more carefully, it is shown that green cluster cases are much less present in the shareholder activation policy option (policy 4) than in the no policy option (policy 0). This indicates negative effects of the shareholder activation implementation on the development of the EVCS price for the red and gold clusters (the least desirable clusters) are primarily present. Gold, green, and red cluster memberships are additionally exclusively present when no policy or shareholder activation is implemented. All 3 clusters do a have a certain similarity in their behaviour: the moments of peaks, dips, and equilibria are at the same points in time, where especially the equilibrium is comparable for red and gold clusters. This implies that a rise in values on the long term is less likely at no policy and even less when shareholder activation is implemented. Since there are multiple cluster memberships at the shareholder activation policy and no policy options (respectively gold and red, and green gold and red) the policy implementations alone are not enough to determine cluster membership and thus to generate specific behaviour. The pairs plots in row 6 show the added influence of the given uncertainties. All added uncertainties except for the initial market share show a similar influence on the outcomes of both policy options. Low parameter values create a large amount of cases for either green or gold cluster memberships, and higher values significantly increase the red cluster membership counts at both policies. In decreasingly influential order this effect is created by the learning curve period EVCS cost, the ROI aim ratio, the progress ratio EVCS cost and the risk premium ratio. In the most left sides of each pairs plot is also clearly seen that especially green cluster membership is due to very low values on there parameters, when combined with the no policy and shareholder activation options. The desirability of the outcome behaviour of no policy and shareholder activation implementation are therefore still very sensitive to investment behaviour differences and economies of scale parameter values. The amount of most desirable cases however is very small and completely dependent of additional large differences in investment behaviour and strong economies of scale effects on the market.



(a) Clustered line plot



(b) Pairs plot

Figure 7.10: EVCS price per kWh filtered findings through time series clustering at defined policies. CID-clustered at $k = 5$.

The no entry alternative is almost entirely responsible for blue cluster membership and additionally creates a majority of the green cases. A first conclusion therefore arises: the no entry policy effects are very desirable on the short-term development of the market prices. The lower cases are generated in this scenario, but only the short-term is desirable because of the steep ascend on the long term for the blue cases, and a moderate ascend for the green cases. Most blue cases increase enough to pass over gold cluster equilibria what makes the long-term outcomes considerably more problematic. The benefit of both cluster memberships being present in the policy scenario is that we can now try and find out the reasons for the steepness of the ascend on the long-term by observing the influences of the other input parameters. The diagonal plots of the uncertainties progress ratio, ROI aim ratio, and the learning curve parameter show that lower values on these parameters correspond to green cluster membership and higher values for blue. Especially the green cluster is significantly connected with low learning curve parameters as shown in cell [5,5]. How this is connected to the no entry policy however is shown through again the policy pairs plots at row 6. The colours blue and green are a bit difficult to distinguish in a dense plot such as these pairs plots, but especially the economies of scale parameters show a clear division of green and blue cases along the axes of the parameters. When economies of scale effects are strong, the long-term outcomes are desirable as well, while on the short-term no differences can be seen. When cost learning curve parameters are low, the price rises again on the long-term. The significance of the added effects of the uncertainties can be seen through all their input pairings: also at pairs plots for ROI aim and risk premium ratio, the lower value areas in the plot combined with other parameters' lower values are predominantly populated by green cases. Restricting market access completely for network companies therefore shows to have a positive influence on the EVCS price development on the short-term, and on the long-term the positive effect is only continuing when high learning curve effects are applicable on the market.

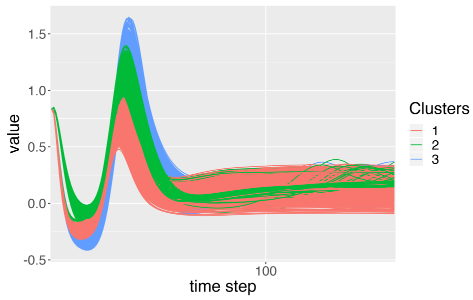
The purple cluster is predominantly caused by the 5 years market entry period policy implementation. The outcomes appear rather robust but relatively high values are present in the ensemble, making it a not very desirable situation. However, since the data-set's clusters are partitioned by distinguishing significantly behavioural differences between the partitions, the effect of the policy on the outcomes is concluded to be very strong. When assessing the pairings of the policy with the learning curve and risk premium ratio, the few green cluster memberships are assigned to those cases with also a low learning curve period and a low risk premium, whereas high values on these parameters cause most of the red cluster memberships in the total cases within the market entry period scenario. These influences are very limited however, for only very little cases within the market entry period scenario have green or red cluster memberships. The temporarily activity policy concept is concluded to be very effective, but does not necessarily result in optimal price development when compared to other options available.

The market share cap set at 50% doesn't appear to be decisive in causing any behavioural differences for the outcomes: cell [7,6] shows that all clusters are rather equally represented in the policy implementation, with a small majority of red and purple cases. The only significant effect can be found when combined with the initial market share as shown in cell [6,1]: the lower initial market share cap combined with a maximum creates outcomes predominantly partitioned into the purple cluster. This implies that when the initial activity of network companies on the market is low, the market share cap increases robustness, but excludes the most desirable outcomes.

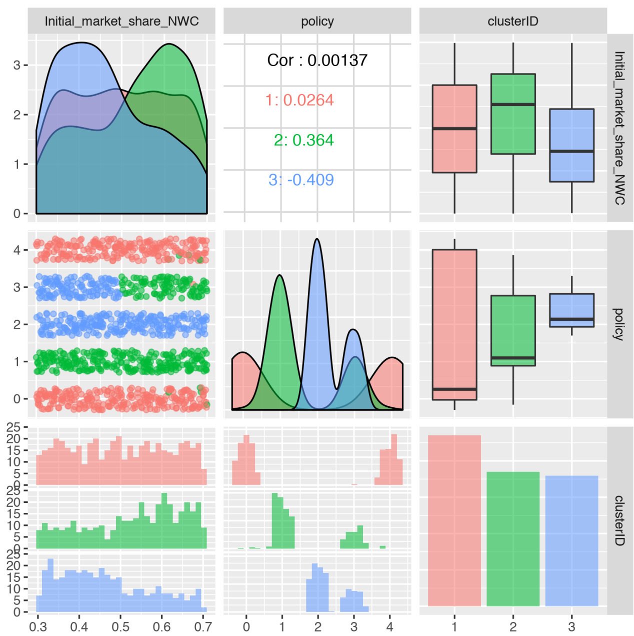
The ROI commercial is partitioned into three clusters with a similar behaviour, but mainly varying in variation and short-term or long-term outcome values (figure 7.11.a):

1. Red: Medium low dip, lowest peak and a large spread covering all values from the most upper- and most lower-boundaries of all outcome space on the long-term
2. Green: The littlest descend, a medium high peak and outcomes cover half of the entire outcome space on the higher half of the values.
3. Blue: Lowest minimum on the short term but also the highest peak values, followed by also higher half values on the long-term similar to the green cluster.

The extreme values in the beginning combined with the long-term outcome spaces makes the green cluster the most desirable grouped outcomes. The blue cluster however has higher values from halfway through the ascend onwards, but the large dip in the beginning may be problematic in early stages of market development. The influences of all uncertainties but the initial market share are not found to be decisive for cluster membership. The red cluster is the result of shareholder activation and no policy, indicating that the shareholder activation action is not very effective. The other policies have a strong influence: the no entry policy results in only green cluster outcomes, the market entry period of 5 years only generates blue cluster cases, and the market share cap is only separated by the range of the initial market share cap. At exactly half the initial value (0.5), the range is blue clustered at low values and green clustered at high values. This implicates the fact that when the market share is implemented, it works more as desired when the network company was



(a) Clustered line plot



(b) Pairs plot

Figure 7.11: ROI commercial filtered findings through time series clustering at defined policies. CID-clustered at $k = 3$.

initially dominant on the market. As a reactive policy measure it is more effective than a prior instrument. The no entry policy however shows to generate the most desirable outcomes.

The defined policies behaviour based scenario discovery has generated insights concerning the impacts of separate policy measures on the system. On the CAPEX gap, EVCS price per kWh and ROI commercial, most policy measures have shown to be very effective. The shareholder activation policy however only slightly influences long-term behaviour of the EVCS price development, where low prices are less likely when it is implemented. Most balanced results on CAPEX gap behaviour are found at no policy, while long-term effects are most beneficial with a market share cap implemented. The EVCS price outcomes showed complex results, for many uncertainties still influence certain behavioural deviations: when no policy is implemented, shareholder activation, or a market share cap is active, most desirable outcomes are very little present and outcomes are highly dependent of uncertainty values. The no entry policy has very positive results on short-term price development, but may lead to strong increases in prices on the long-term due to interactions with high learning curve parameters (low learning curve effects). For the ROI estimations of commercial parties, it is clear that the absence of a network company on the market results in a more attractive investment climate on the market for commercial parties, and setting the market share cap at 50% shows to be most effective when implemented as a reactive policy (lowering the market share of a network company in later stages).

7.4.2. Mixed policies

Cluster counts are found through assessment of silhouette widths which has created the following results:

Cluster counts

- CAPEX gap k=4
- EVCS charging price: k=3
- ROI Commercial: k=2

The CAPEX gap will again be reviewed first (figure 7.12). A first interesting observation is the insignificance in behaviour deviation created by the market entry period. The Sobol analysis showed a strong sensitivity to the variation of the market entry period on the CAPEX gap, but for behavioural clustering there is no correlation found between cluster membership and the market entry period. The red cluster is completely assigned to situations with no entrance, creating the clear downward sloping curves. The red and blue clusters however are interesting: the green cluster still contains some positive values which are not desirable, and the blue cluster contains cases that have a very strong dip in the beginning but still recover considerably towards the end. When the no entry policy is not implemented, the market share cap shows to be very decisive for distinguishing blue and green cluster memberships as seen in cell [2,1]. The low market shares result in the blue cluster up to a value of about 0.3. Interestingly enough, this separation suggests that the effects of the fixed market share cap in the defined policy analysis were less decisive due to the fixation at 0.5 which is too high for it to be effective enough to reduce all cases to below 0. In the other pairs plots, the red dots in the spectre should be ignored for these cases are solely the result of the no entry policy. When looked at the separation in cell [3,2], it shows a very mild interaction of the market share cap with the initial market shares: lower initial market shares for network companies have only a few blue cases at very low market share caps, and higher initial market shares have increasingly more blue cases at gradually increasing market share caps. From a policy-maker's perspective, this means that either restricting network companies from entering the market or setting a market share cap rather low can lead to desirable results. Although strong resistance would be expected, the results show that even with extremely low market share caps, the cost advantages of commercial parties are relatively low on the long-term.

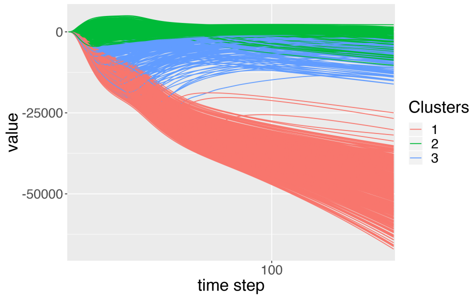
The EVCS price per kWh at mixed policies again shows interesting results. It is now clustered into 3 clusters as shown in figure 7.13. The 3 differences in behaviour are mainly the equilibrium differences between the green cluster and the others: the blue and red cluster values increase on the long-term and green cases stabilize quicker. The desirability is difficult to say, for the equilibrium of green values is desirable in terms of behaviour, but there are some considerably high outcomes in it and there is a very large spread of outcome values.

The no entry switch has one very clear effect on price development: no entrance results in low values and ascending prices on the long term (no green cases). The presence of both parties on the market therefore is suggested to contribute to finding a price balance on the market quicker, but may also lead to higher prices overall. This also suggests that lower prices are created when commercial parties are solely allowed on the market. A clear reason for the distribution of higher outcome values and lower is seen in cell [5,5] of figure 7.13.b. The learning curve parameter creates a significant difference between either blue or other cases. Combined with the no entry switch (cell [5,1]), the learning curve has a very dominant influence and at a high learning curve period or a slow cost development rate, restricting network companies from the market has a negative effect on long-term price development.

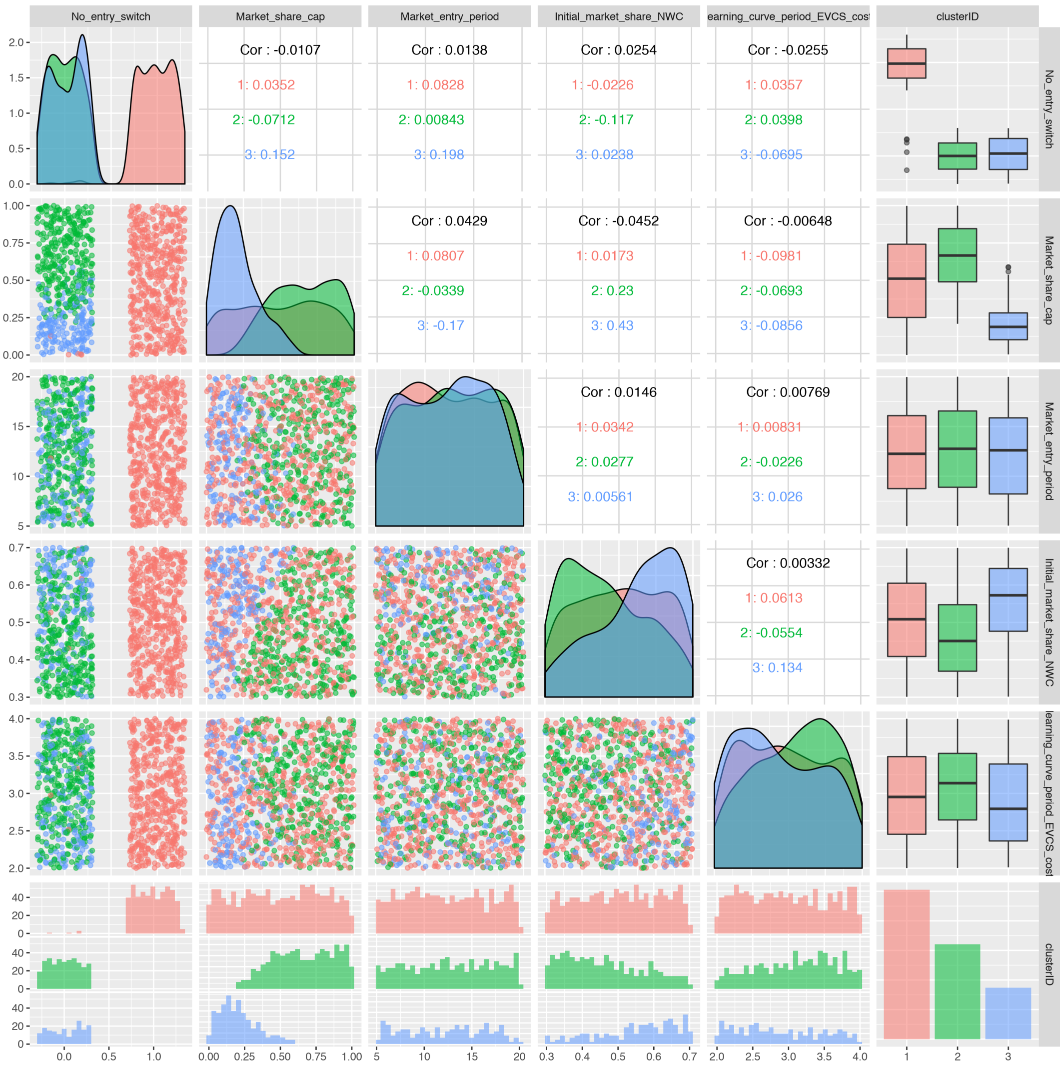
The market share cap also effects the outcomes slightly. A higher market share cap results in more green cases, whereas both red and blue cases are mostly present at low market share rates. This adds to the notion suggested in the previous paragraph of both parties being present leading to a price equilibrium faster: more freedom for a network companies leads to an earlier price balance. This also implies that either both parties should be active or the network companies should be dominant for the market to reach an early equilibrium.

Figure 7.14.a shows the differences per cluster: the red cluster contains all highest peaks and rather stable, high values over the end period. The aquamarine cluster however contains low values in the beginning and appears to show increased oscillating behaviour on the long term. Policy levers no entry and market share cap are accounted for most of the ROI commercial outcome behavioural differences. Figure 7.14.b shows through column 1 that all aquamarine cluster members are absent when the network companies are excluded from the market, which supports the general notion of a network company being unfair competition on the market and disrupting the market by decreasing profitability. The same is seen with the market share cap in column 2 and cell [2,1]: a market share below 0.25 excludes aquamarine cluster membership. The policy measures prove to be predominantly influential on the ROI commercial development as the pairs plot in cell [4,3] shows that however showing small effects when combining initial market shares and learning curve periods, a seemingly uniformal distribution is observed.

Behaviour based scenario discovery showed some interesting results regarding the behaviour of the outcome trajectories at mixed policy implementations. Price development reaches an equilibrium faster when network companies are either equally or more dominantly active on the market than commercial parties, although prices are lower on the short-term when the opposite is the case. Additionally, ROI estimations for



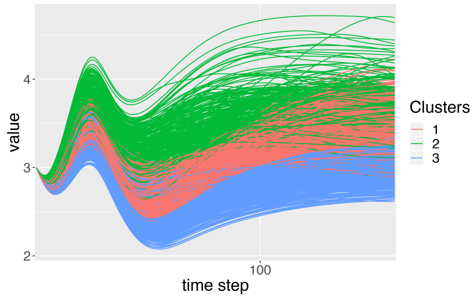
(a) Clustered line plot



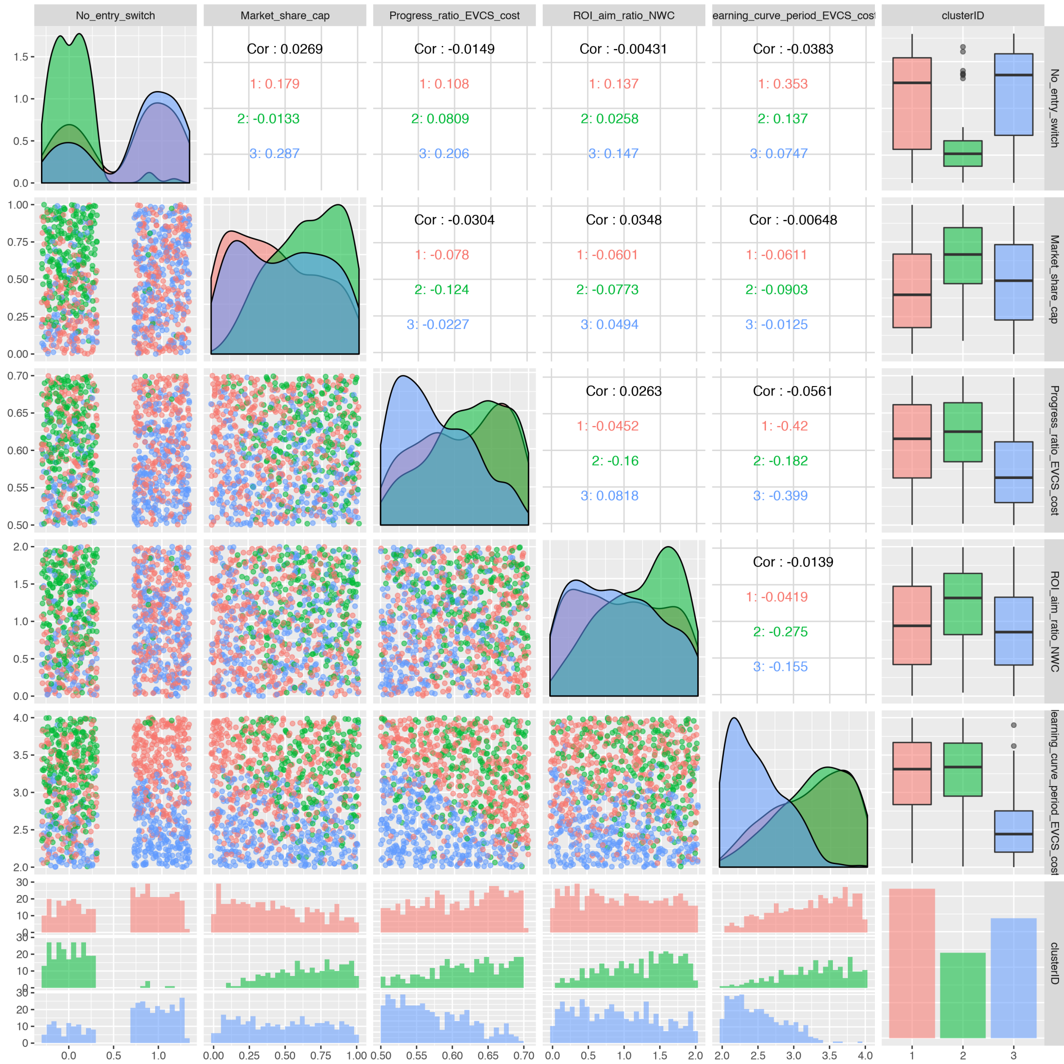
(b) Pairs plot

Figure 7.12: CAPEX gap filtered findings through time series clustering at mixed policies. CID-clustered at $k = 3$.

commercial parties is most positive when network companies are allowed no entrance to the market or when allowed to operate up to a market share below 25%, and the long-term results when granting more freedom for network companies on the market are very uncertain. From the CAPEX gap it is shown that again lower market share caps have a significant effect, but what is even more interesting is that it shows that cost advantage differences, when in the advantage of the commercial parties, still recover significantly after very low values of the CAPEX gap. Conclusively, development differences can mostly be made by either excluding the network companies from the market or limiting their activity intensity, and that exclusion of network com-



(a) Clustered line plot



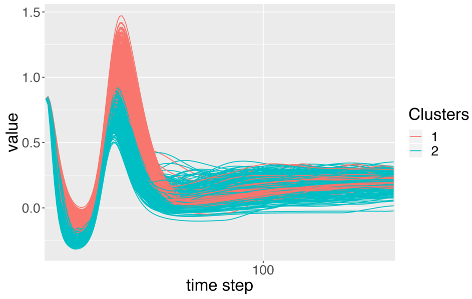
(b) Pairs plot

Figure 7.13: EVCS price per kWh filtered findings through time series clustering at mixed policies. CID-clustered at $k = 3$.

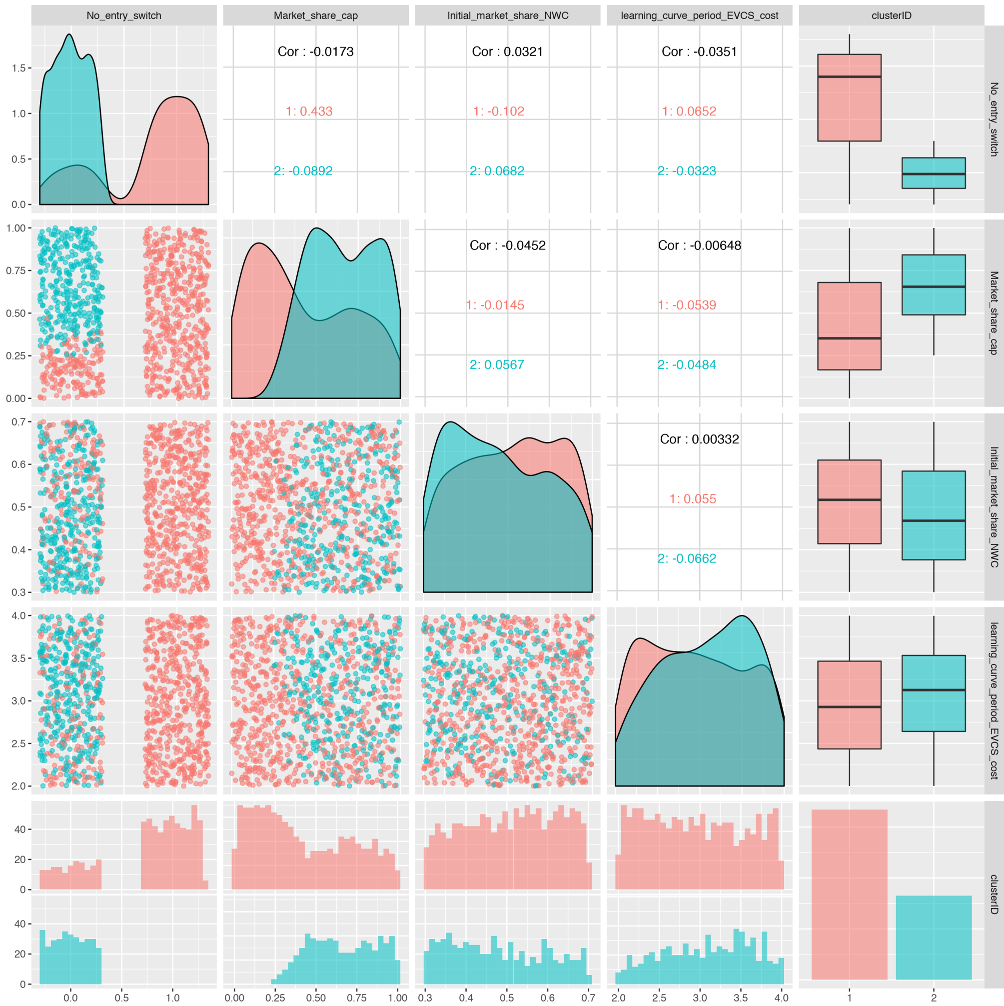
panies on the market generally has negative effects on long-term price development, but positive effects on short-term prices and on general profitability for commercial parties.

7.5. Behaviour based scenario discovery conclusions

The results have shown that shareholder activation is not an effective policy for influencing EV charging infrastructure market development. Additionally, temporary market entrance has shown very limited effects on the outcome behaviour of all KPI's. The remaining policy strategies, no entrance or a market share cap, have



(a) Clustered line plot



(b) Pairs plot

Figure 7.14: ROI Commercial filtered findings through time series clustering at mixed policies. CID-clustered at $k = 2$.

however proven to be very effective, but do come with again a strong trade-off between price development and ROI development effects. Limiting or restricting the activity of network companies on the market leads to higher prices, but robust and higher profitability for commercial parties. The effects of an implemented market share cap however do only show to be effective when set considerably low: below 25%. The intensity of learning curve effects and profit target differences cause very low initial but also rising charging prices on the long-term, which is not mitigated by the mentioned policy implementations.

Mentioned effects on the profitability of investments on the market for commercial parties and price development are both equally important, but price development outcome ensembles are considerably less robust than the ROI outcome space. Prioritising these outcomes is therefore recommended, but it must be considered that an ROI equal of less than 0 is a significant entrance barrier for new entries.

7.6. Policy analysis conclusions

In this chapter the outcomes of the modelled system are analysed with various implementations of the role demarcation policy options. Two different approaches have been explored: individual and fixed implementations, and mixed implementations of the policies. The effects of the different strategies have been analysed through sensitivity analysis and behaviour based scenario discovery.

A primary important conclusion regards the effectiveness of the different policy options: shareholder activation has shown not be considerably effective. Setting a market entry period has only shown to increase robustness of the ROI outcomes in the exploration phase. Completely restricting market entrance for network companies has shown to be very effective, as well as setting a rather low market share cap at a maximum of 25%. The effective policies show a clear trade-off on price and ROI development when implemented.

Short-term effects of the policy implementations are most significant: limiting or restricting network companies' activities leads to higher EV charging fees, but also higher ROI estimations for commercial parties. On the long-term, these effects are heavily amplified and influenced by interaction effects with economies of scale parameters and investment behaviour differences. More specifically, the stronger the market specific dynamics, the more prices tend to increase between 2020 and 2030.

Conclusively, setting a low market share cap or restricting entry for network companies lowers market entrance barriers and increases attractiveness of the market for commercial parties, but estimated charging fees will develop towards higher prices. On the long-term, the EV charging fees outcomes are additionally heavily influenced by market specific cost reducing dynamics.

8 Discussion

In this chapter all results will be discussed, from model generation to the effects of policy implementations. The EVCS development model and the analysis process will be discussed first, aimed at identifying complications and possible limitations of the research. In section 8.2, the conclusions from chapters 5 and 6 will be discussed: how useful are the results and what do they imply? All identified subjects for discussion have additionally been discussed with various groups of policy experts from both the Ministry of Economic Affairs & Climate Policy and the Ministry of Finance (Appendix A). All relevant insights will be presented and here.

8.1. EVCS market development model & analysis process

The market development that has been analysed is the fundamental result of how the EVCS market development model has been built. It is important to discuss the assumptions, simplifications, and complications of the model development process to highlight possible shortcomings and implications of the final outcomes.

First of all, the market party distinctions were a main challenge. Since market development is considered to be a direct result of the activity of market parties on it, it has been a complicated decision whether to simulate more market parties or maybe even model the market as a whole, without direct distinctions between individual market parties. The first option has been discarded for conceptual reasons: the effects of network companies acting on the market are highly conceptual and generally only researched by either a very theoretical or by an extremely delineated approach. This makes actual effects very hard to find and many assumptions must be made for such a construction to represent a realistic scenario when individual market parties would be modelled more specific. Additionally, when modelling many different market parties it only makes sense when these market parties are significantly different as well, adding even more detail to the concept. Finally when detailed enough, the market parties' behaviour on a large aggregate scale such as market development on a national level basically functions as a group with average characteristics that account for the most significant influences. Thus, the chosen approach to aggregate the market parties into 2 functioning composite actors is believed to be optimal for both practical and theoretical reasons.

A second complication arises with the uncertainties in dynamic structures such as learning curves or development curves. These structure can have large influences on a system, depending on the parameter values of the curves. The estimation accuracies are less relevant in this case, since the parameters are sampled and their possible influences are examined rather than used to predict the future. However, even this approach has its complications. Learning curve effects, mainly the cost reducing kind, proved to be of very significant influence on almost all results. This is a valuable finding, however the learning curve parameter range could affect these outcomes: when the range would have been expanded, the influences would be even greater in some scenarios. This creates an important trade-off: the wider the range, the more uncertainty is simulated and thus creates a larger and more complete picture of the possible outcome space, but the more dominant the parameter will become which increases determinism of the research outcomes. The accuracy or realism of the uncertainty parameters can never be judged perfectly, making it a possible source of error. Although this will always remain a valid subject for discussion, in this research particularly a lot of effort has been put into the attempt to approximate the most usable values. Finally, even though ranges could be set smaller or greater, the main goal is to find how much uncertainties influence the system in relation to other uncertainties and all ranges here are set proportional to others, creating the most valid results concerning uncertainty influences.

A limitation regarding the SD model that should be mentioned is the absence of feedback effects of policies influencing the behaviour indirectly instead of directly. When the policy-maker would assign a market entry period limit or set a certain market share cap it is not unthinkable that the network company could respond by not entering the market at all. Modelling less direct behaviour of market parties has been found to be incredibly complex and many approaches for it are very debatable when attempted to quantify, which has excluded this from this research. Adding to previously mentioned complications of the resolution of the model, including such behaviour would be more relevant when increasing the model's resolution. However, the insights created by the presented research provide useful insights concerning direct behaviour, which is considered to be sufficient for the main research goals. Additionally, attempts to model indirect behaviour as well would significantly add to the model's complexity and uncertainty, where the chosen approach is believed to be more balanced.

Concerning the analysis process, a first remark should be made in relation to the outcome space. The outcome parameters are carefully considered, developed, and evolved throughout the entire research to allow a comprehensive picture of the market development and the effects of uncertain variables and policies on it. During the analysis, the consecutive steps of the analysis resulted in a sequential filtering process regarding the outcomes to be analysed: the exploration phase during the model analysis identified the insensitivity of the amount of EV charging stations relative to the amount of BEV sales, the BEV sales share itself showed to be insensitive towards all uncertainty and policy ranges other than the ones part of the vehicle development structure, the market share outcomes were concluded to be irrelevant during the policy analysis, and the CAPEX gap outcomes show limited insights regarding policy impacts. Out of 6 kpi's to start with, only 3 remained for the final stages of the policy analysis. I believe that the filtering process serves as a significant addition to the conclusions of the research, since it highlights the relevance of certain outputs concerning the problem at hand. The EV charging infrastructure market development is found to have very little impact on the BEV sales until 2030, the demand side of the market is expected to be sufficiently satisfied in all cases, and the market shares are only relevant to monitor when no policy is applied. For the policy analysis, the most important conclusion is the importance and sensitivity of the price development and the profitability development for commercial parties.

The different approaches of the Sobol sensitivity analysis and the behaviour based scenario analysis are found to positively complement each other. The Sobol indices provide very clear information regarding the influence of each parameter on the outcome values, whereas the behaviour based scenario discovery results show how the parameters influence the actual development of the outcomes over time. For a research focused on development this has found to be very useful. Additionally, testing sensitivity on various points in time has provided very significant additional insights regarding the development process. However, both are rather novel approaches which have some challenges in applicability. The time series clustering method is very useful for subspace induction, but more information can be derived from the data when digging deeper into the clustering procedure. Right now, the clustering procedures are still somewhat arbitrarily: cluster counts selection is partially a subjective process and the clustering algorithm is visually selected. Although the arbitrary steps are considered to be not only valid but also necessary for finding desired results, the decisions made in the process are difficult to formally validate and require comprehensive descriptions to create sufficient understanding. Additionally, the arbitrary steps in the process combined with the necessity of extensive reasoning during that process itself and the computational expense of the analyses makes it a very time consuming and labour intensive procedure.

8.2. Results

Policy analysis and especially base case analysis both showed very straightforward conclusions concerning the interaction of the EV charging infrastructure market and the vehicle market. The infrastructure market clearly "follows" the vehicle market very well, but opposite feedback effects were not significant. EV development is therefore within the scope of role demarcation strategies an independent driver for the EV charging infrastructure market. The ideal charging stations to BEV rates is based on research's that concluded that there would always be a demand for about 1 charging station per 4 BEV's, which is always satisfied in all scenarios as well. Although the results in this research mean indicate no feedback effects, it is important to note that these effects being absent is the result of the demand being satisfied in all scenarios: when the demand would not be satisfied, it is highly expected that BEV sales would be influenced. The expected demanded EVCS to BEV ratio is partially based on the theory that when greater numbers of people would own BEV's, about 25% of them would not be able to own private charging connections and therefore will be entirely dependent of public charging stations. Conclusively, the results of this research show on EVCS and BEV market interactions that when the demand for public charging stations is satisfied, the EV infrastructure market development does not influence the BEV market and in all simulated scenarios that demand is satisfied.

Regarding policy implementations, most clear results were shown on effectiveness of the policies: shareholder activation is not effective and setting a market entry period only results in slightly increased robustness and desirable outcomes for the profitability on the market for commercial parties. Shareholder activation is basically an attempt of the national government to align their goals and intentions with local governments. From the network companies' perspective, it is stated to be experienced as a passive aggressive approach because they desire and expect more direct communication with the responsible Ministry (Interviews Alliander and Ministry of EA&CP). The fact that this approach may therefore harm the relationship between the Ministry and the network companies combined with its ineffectiveness thus implies this option should not be considered as a plausible strategy. The market entry period, simulating the idea of defining a temporary activity for network companies, does however show useful effect considering the initial and fundamental goals of the Wet VET: facilitating the ability of network companies to act on the desired market, while fair competition on the market is maintained. Setting a temporary activity results in a more robust and slightly more positive development of profitability for commercial parties, while not influencing other market outcomes of interest. However, because the effects are limited the decision-maker should consider these results in relation to the costs, effort, and possible effects on stakeholder relations of the policy implementation carefully.

The most effective policy measures are concluded to be setting a market share cap or entirely excluding network companies from the market. Setting a low market share cap or restricting entry for network companies lowers market entrance barriers and increases attractiveness of the market for commercial parties, but estimated charging fees will develop towards higher prices. On the long-term, the EV charging fees outcomes are additionally heavily influenced by market specific cost reducing dynamics. These findings are quite similar to the base case analysis outcomes which indicate a similar trade-off on price and profitability development, but caused by underlying market dynamics completely. The most influential policy measures therefore create a challenging dilemma for the decision-maker who is forced to prioritise desired market outcomes. Adding to the complexity of the dilemma, the trade-off between price development and commercial party profitability is in line with a most relevant issue on the subject of energy policy: the tension between free market theory and the more technical system perspective (Interviews Alliander, Enexis, Ministry of EA&CP, and Cogas: Appendix A). Lower prices indicate a more efficiently functioning system resulting in cost-efficient production (Künneke and Fens, 2007; Künneke and Finger, 2009), and more profitability for commercial parties increases the attractiveness of the market for commercial parties which increases fair competition. Network companies typically favour optimisation of the system, and the Ministry of Economic Affairs and Climate Policy generally strives for free market scenarios. In an attempt to aid further decision-making with respect to this dilemma, an important nuance is added through the research findings: price development differences are much larger than profitability differences and significant effects of underlying uncertain market dynamics are considerably little on the short-term. In developing a certain strategy, this implies two very important notions. First, the decision-maker should be aware that negative effects of restricting or limiting access on the market for network companies on price development are an order of magnitude larger than positive effects on profitability. Second, the most significant uncontrollable effects of uncertainties occur after a considerably long period of time, granting the decision-maker some opportunity to adjust previous decisions when more accurate predictions can be made due to the increasing availability of historical and empirical data.

Finally, all subjects of discussion raise the most important question of all: "Should we implement role demarcation policy on this market?". Within the boundaries of this research, this question cannot unambiguously be answered. However, an important contribution towards finding an answer to this question is presented: Limiting or restricting activities of network companies on the market moderately affects short-term market development. The first period of a market development cycle is generally the most decisive period for shaping total results (Deszca et al., 1999). Although all long-term outcomes are heavily influenced by uncertainties and policies have proven to provide no robust long-term outcomes, the first period is still of great importance. The decision-maker should therefore focus on the short-term effects, prioritise the outcomes of interest, and thereby select an appropriate course of action. When prioritisation is impossible or a balanced dilemma still remains after prioritisation, this might imply that implementing no policy at all would actually be the most suitable action.

9 Conclusions

In the following, the answer to the research question and the most relevant conclusions of the research will be addressed. The main research question is stated as follows:

How does role demarcation policy influence the development of the electric vehicle charging infrastructure market in the Netherlands?

To answer this question, an Exploratory System Dynamics Modelling and Analysis approach has been followed. A System Dynamics model is created to simulate the possible development paths of the electric vehicle charging infrastructure market over a period of 20 years from 2010 until 2030. Key dynamics and uncertainties have been identified and implemented in the model and a complete outcome space has then been generated and analysed by applying sensitivity analysis through Sobol indices at various moments in time and behaviour based scenario discovery through time series clustering.

Differences in investment behaviour between commercial parties and network companies, the vehicle market, and EVCS market specific dynamics drive the variation of the EVCS market outcomes. The EVCS market development system is therefore based on a System Dynamics supply-demand-price concept and is further expanded using 3 different structures: vehicle development, EVCS supply, and market party investment behaviour. Access to financial capital, risk valuations, and profit targets are identified as main drivers for investment behaviour differences. The dynamics driven by external factors and uncertainties that influence the system are vehicle development, cost reduction learning curves, and technology development learning curves. The key performance indicators for market development are price development, entrance barriers and demand satisfaction of which the critical entrance barriers are found to be cost advantages and capital requirements. Price development is measured by monitoring the added charging fee per kWh, the cost advantages are measured by calculating the differences in capital expenditure for new projects between the different market parties, demand satisfaction is measured by taking the number of public EV charging stations relative to the number of EV's on the vehicle market, and capital requirements and market attractiveness is analysed by measuring the expected returns on investment of commercial parties when maintaining marginal prices. The resulting model has been validated through face validity and comparison with existing research outcomes and models.

Both the sensitivity analysis and behaviour based scenario discovery showed a difference in short-term (2010-2020) performance and long-term performance (2020-2030), where behaviour and values were considerably consistent within these separate periods. An important distinction is thereby made between short- and long-term performance and several trade-offs have been identified.

Concerning the feedback effects between the charging infrastructure and the vehicle market, the results show that when the demand for public charging stations is satisfied, variations in EV infrastructure market development do not influence the BEV market. Additionally, in all simulated scenarios the charging infrastructure demand is satisfied, allowing no certain statements on completely discarding feedback effects from the charging infrastructure market but also indicating satisfying and sufficiently following market development behaviour. Other market dynamics in the system have however shown much stronger influences on the system: larger investment behaviour differences between network companies and commercial parties result in lower prices, but market attractiveness is significantly disrupted as well. Economies of scale and technology development effects tend to amplify these consequences increasingly over time.

From the various policies that have been implemented, the shareholder activation is concluded to be ineffective. Setting a certain market entry period, as is currently done by using temporary activity measure, has only little effect on the attractiveness of the market: the outcome space becomes more robust and ensures at least the possibility for commercial parties to break-even when investing on the public EVCS market. The temporary task is therefore considered to be successful in fulfilling its intended purpose, but its limited effect should be considered when deciding to use the instrument. Other factors such as process costs and possible effects on stakeholder relations may outweigh the eventual effect of the policy measure on the market.

The most effect policies are complete restriction of network companies on the market or setting a maximum market share for network companies. Setting a low market share cap or restricting entry for network companies lowers market entrance barriers and increases attractiveness of the market for commercial parties, but estimated charging fees will develop towards higher prices. On the long-term, the EV charging fees outcomes are additionally heavily influenced by market specific cost reducing dynamics. The most influential policy measures should therefore be aimed at directing the market development on the short-term only, and additionally create a challenging dilemma for the decision-maker who is forced to prioritise desired market outcomes. Adding to the complexity of the dilemma, the trade-off between price development and commercial party profitability is in line with a most relevant issue on the subject of energy policy: the tension between free market theory and the more technical system perspective. Lower prices indicate a more efficiently functioning system resulting in cost-efficient production, and more profitability for commercial parties increases the attractiveness of the market for commercial parties which increases fair competition. Network companies typically favour optimisation of the system, and the Ministry of Economic Affairs and Climate Policy generally strives for free market scenarios. In an attempt to aid further decision-making with respect to this dilemma, an important nuance is added through the research findings: price development differences are much larger than profitability differences and significant effects of underlying uncertain market dynamics are considerably little on the short-term. In developing a certain strategy, this implies two very important considerations:

1. *Negative effects of restricting or limiting access on the market for network companies on price development are an order of magnitude larger than positive effects on profitability.*

2. *The most significant and uncontrollable effects of uncertainties occur after a considerably long period in time, granting the decision-maker the opportunity to adjust previous decisions when more accurate predictions can be made due to presumably increasing availability of historical and empirical data.*

Finally, the presented findings raise probably the most important question of all: "Should we implement role demarcation policy on an emerging market?". Within the boundaries of this research, this question cannot unambiguously be answered. However, the results do contribute towards finding the answer to this question is: Limiting or restricting activities of network companies on the market moderately affects short-term market development. The first period of a market development cycle is generally the most decisive period for shaping total results and the decision-maker should therefore focus on the short-term effects, prioritise the outcomes of interest, and thereby select an appropriate course of action. When prioritisation is impossible or a balanced dilemma still remains after prioritisation, this might imply that implementing no policy at all would eventually be the most suitable action.

10
Reflections and future recommendations

In this chapter, the research will be reflected on and evaluated. Societal and academic relevance of the research will be discussed, the research process will be evaluated, and directions for future research will be presented.

10.1. Societal relevance

The research is conducted to specifically address a relevant and actual problem where the Ministry of Economic Affairs and Climate Policy is working on at the moment. The role demarcation challenges on new energy infrastructure in specific relation to network companies is a heavily discussed subject with very significant societal impact. Optimising the performance of energy infrastructure markets while preventing abuse of market power is not only complex but also of great essence in our society. The discussion concerning the subject is so far very opinion-heavy and pragmatic with arguments of still a very conceptual nature. Providing more synthesized and measurable insights is therefore considered to be of significant value and is expected to provide a more stable foundation for decision-makers to develop specific strategies.

On a more aggregated level, this research touches upon the key challenges in developing policy strategies on emerging markets. The ongoing energy transition is one of the most important goals of our society at the moment, and its effects create challenges as well. To facilitate the energy transition as optimal as possible, it is important to know challenges and opportunities of developing future-oriented policies.

10.2. Academic relevance

A fundamental problem that has shaped the directions for this research is the lack of consideration of effects of uncertainties on the development of new energy infrastructure markets. By researching and taking into account the effects of uncertainties, this research contributes by exploring market development in a wider context where outcomes are less dependent of assumptions. The findings therefore provide a more complete picture of possible market development paths.

Second, the chosen subject of role demarcation policies on new infrastructure markets is not yet specifically researched in a complete context. The available research is generally more theoretical or conducted through a very limited scope. Actual synthesis of available theories and data is missing. More specifically, the electric vehicle charging infrastructure market is widely discussed but still available research is limited and is usually either a very technical product evaluation or again a very theoretical approach. This research is the first attempt to analyse the electric vehicle charging infrastructure market development system as a whole while taking into account both various relevant theories and more product specific factors.

Finally, the chosen methodology is considered to be scientifically relevant for its novelty. Using Sobol indices for global sensitivity analysis is relatively new and applying it to various moments in the simulated period in order to allow dynamic sensitivity analysis is also no conventional approach. Especially behaviour based scenario analysis through time series clustering is a very new approach: to my knowledge, this research is the very first application of time series clustering in the assessment of an actual, real-world problem.

10.3. Research process evaluation

Independently conducting research and extensively reporting on this research has proven to be both inspiring and challenging for me. Especially working on a real case has been a very strong inspirational factor throughout the process. Working together with policy experts from the Ministry of Economic Affairs and Climate Policy, regular discussions with highly relevant stakeholders, and using the skills that I have learned during my education to deliver relevant contributions myself from time to time has motivated me constantly. Since the first year of my BSc programme (Technische Bestuurskunde), it has been my ambition to apply the skills that I had learned or would learn to actually contribute to real challenges related to the energy transition. I am very glad to have been granted the opportunity to finally do so by conducting my final graduate research project at the Ministry of Economic Affairs and Climate Policy.

The market organisation topic itself is a very interesting and highly complex subject. The complexity has also both inspired and challenged me: the biggest challenge to my experience during the research process has been demarcation of the research. The subject is so large that every demarcation felt like another step towards less relevant outcomes of the research. This challenge has delayed the initial kick-off of the project a little, but fortunately with some help from my supervisors I believe the final presented research has resulted in an academically consistent product and contributes considerably in assessing current market organisation problems.

Regarding the research methodology, I have found great pleasure in applying very novel methods. Especially behaviour based scenario discovery through time series clustering and some sensitivity analysis adjustments are, to my knowledge, very state-of-the-art approaches. Having little to no exemplary research to refer to when difficulties arise has been very challenging, but the added uniqueness to the research has been very satisfying as well.

Finally, it has been a pleasure working at the Ministry and I have learned a lot in the past period. Besides conducting my research and discussing this frequently and extensively with policy experts working on similar subjects, I have been given the opportunity to constantly be involved in the most actual and relevant challenges concerning energy policy. From helping with the development of the new energy law (Energiewet 1.0) to supporting the Minister himself during parliamentary debates I was not only allowed, but encouraged to participate in the process. As a result, I look back to a period where I did not just conduct my final research, but where I also have gained a vast amount of additional knowledge and experience.

10.4. Future recommendations

As mentioned in the results discussion, the research provides guidelines and insights on how role demarcations work and what factors mainly influence the development of the EV charging infrastructure market. Other complications that result from the aggregation of the model are highlighted in the model discussion as well. Four interesting options for further research are suggested based on the limitations and implications of this research's outcomes:

- Simulation of the system on a smaller time-scale: Initial, very short-term decisions made by the different market parties has shown to have a mentionable influence on further development of cost advantages or market power distributions. Although mainly relevant regarding no policy scenarios, it is expected to provide meaningful insights when the very first innovation period is assessed. A more detailed model would be needed in order to find these insights, as well as a much smaller time-step should be set.
- Increasing the resolution of the model: The model can be supported by more detailed market party behaviour structures and for instance agent based modelling can be used to create many different agents acting instead of the two aggregated market classes. Additional accuracy and more detailed outcomes may result from this and the investment behaviour can be investigated further, including the exploration of possible more nuanced investment behaviour influencing policies. Also more localised simulations can provide important insights for local governments because it is plausible to assume that infrastructure markets such as EV charging infrastructure develop different in different regions.
- Indirect behaviour research: As mentioned in the discussion, indirect behaviour effects are not included in this research. However, expectations, relations, and perceptions of different market parties

are expected to affect the system outcomes as well. Additionally, when recommending an expansion of this research, it would also be useful to research the effects of EVCS price development on society to support the possibility to make decisions concerning the presented trade-off on the EVCS market.

- Finally and more focussed on the methodology of the research: the time series clustering method is a very novel approach and still has some debatable aspects. This research is, to my knowledge, a first application of the method on a real-world problem and it has shown some areas of improvement. Further research on the development of the application of this method is therefore advised, with the focus on possible improvements of clustering method and cluster count selection methods.

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A
Expert Consultations

Table A.1: List of experts who have been consulted during the research. Experts who have expressed the desire to remain anonymous or who have not yet given permission for the publication of their names are marked as *Anonymous*.

Organisations	**Name**	**Function**	**Topics**	**Venue**
Ministry of Economic Affairs & Climate Policy	Martijn Koolen	Team leader net management	General research related	Weekly meetings team net management, bi-weekly personal meetings
Ministry of Economic Affairs & Climate Policy	Aurél Kennesey de Kenese	Senior policy officer net management	Allego, Hydrogen infrastructure market role demarcation	Weekly meetings team net management, personal meeting
Ministry of Economic Affairs & Climate Policy	Han Feenstra	Senior policy officer energy innovation	Hydrogen infrastructure market role demarcation	Department of Energy and Innovation - Strategic consultation
Ministry of Economic Affairs & Climate Policy	Paul Claassens	Policy officer energy innovation, former employee Alliander public affairs	General relationships Alliander - EA&CP	Personal meeting, informative session team net management
Ministry of Economic Affairs & Climate Policy	Bjørn Volkerink	Senior policy officer General Economic Politics	Role demarcation policies, general vision and approach EA&CP	Personal meeting
Ministry of Finance	Marcel Boere	Specialist Stateshareholderships	Shareholdership State - TenneT	Personal interview
Ministry of Finance	Alexander van Boxtel	Specialist Stateshareholderships	Shareholdership State - Gasunie	Personal interview
Authority Consumer & Market	Vincent Lindijer	Specialist monitoring and market supervision - Energy department	Allego, general market supervision	Personal interview
Alliander, Liander	*Anonymous*	Multiple attendees: Advisor venturing & innovation, Director asset management, Liander managers	Alliander challenges and side activities	Meeting EA&CP - Alliander
Enexis	*Anonymous*	Multiple attendees: Head of public affairs, Strategic manager Grid Operations	Enexis challenges and side activities	Visit EA&CP - Enexis
Eneco	Dioni Franken	Advisor Strategy	Future market projections	Visit EA&CP - Eneco
Limburg Province	*Anonymous*	Head of shareholderships	Shareholdership Limburg - Enexis	Visit EA&CP - Enexis
Netbeheer Nederland	André Jurjus	Director	General net management challenges and desires	Various formal occasions
Cogas/Coteq Netbeheer	*Anonymous*	Executive Secretary and Director of Distribution Services	Coteq acitivity expansions and permitted tasks	Formal meeting
TU Delft	Willem Auping	Lecturer & Researcher	System Dynamics and ESDMA	Multiple personal meetings
TU Delft/Wageningen Universiteit	Patrick Steinmann	Alumni/PhD Candidate	Time Series Clustering	Frequent correspondence

B

EVCS Development Model

B.1. Vensim model views

B.1.1. EVCS development cycle

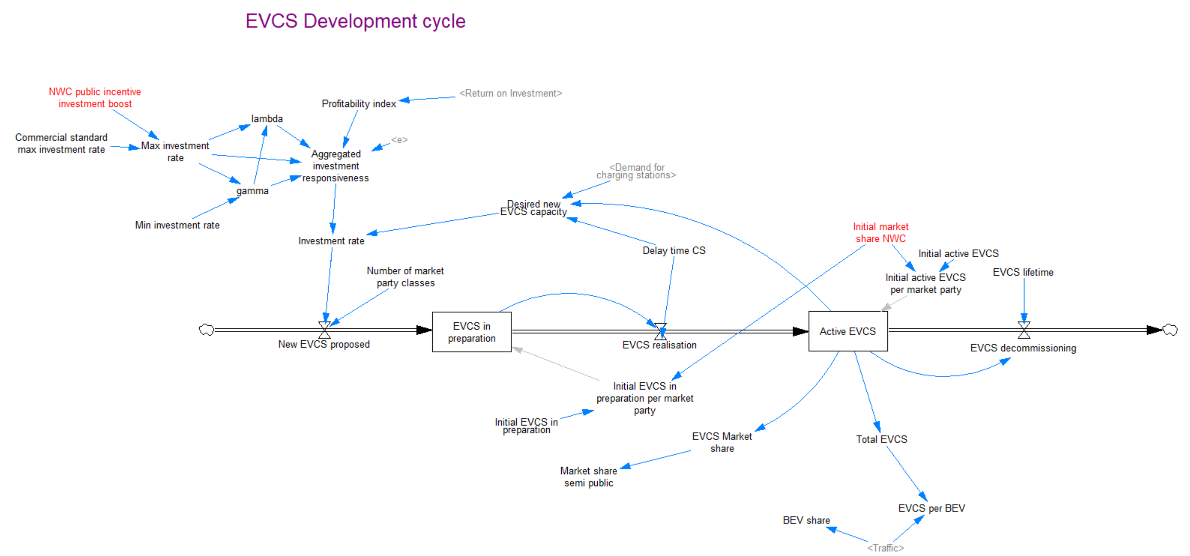


Figure B.1: A snapshot of the model's EVCS supply structure in Vensim.

B.1.2. Vehicle development

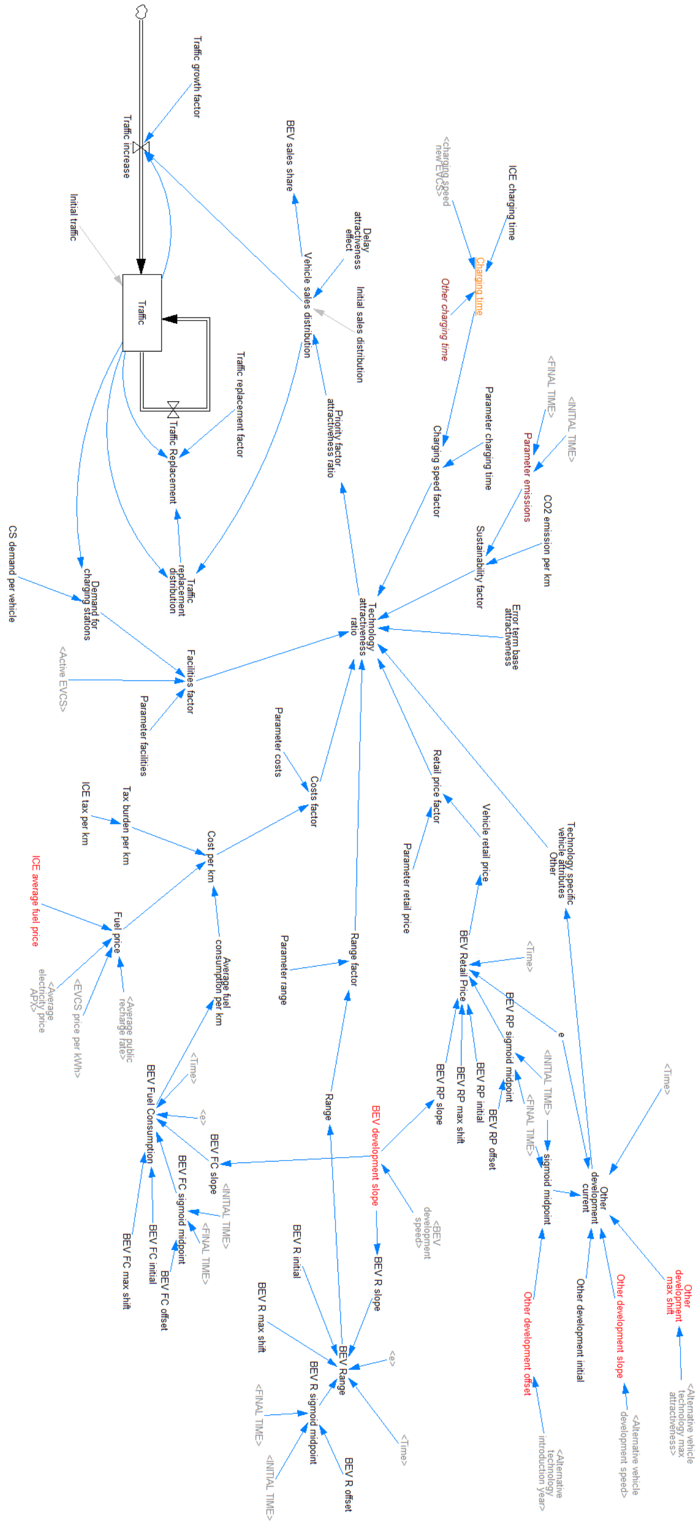


Figure B.2: A snapshot of the model's vehicle development structure in Vensim.

B.1.3. EVCS returns

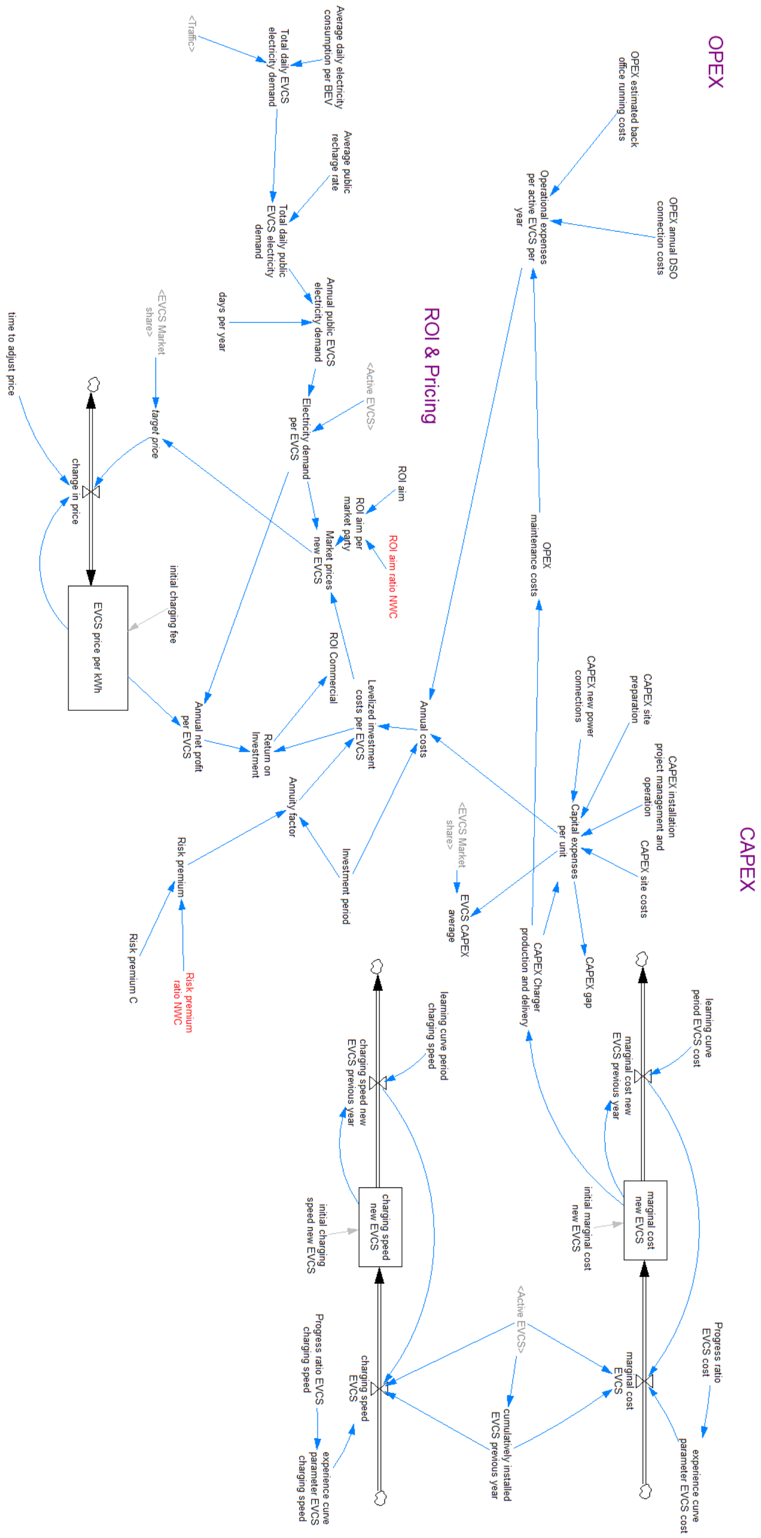


Figure B.3: A snapshot of the model's EVCS returns structure in Vensim.

B.2. Constants & parameters

B.2.1. EVCS supply structure constants & parameters

Table B.1: Constants with corresponding values, units, and literature references for the EVCS supply structure. Uncertainty parameters shown in red, policy levers shown in green.

Constant	Value	Units	Reference
Initial EVCS in preparation	200	Charging Stations	(RVO, 2018)
Initial active EVCS	200	Charging Stations	(RVO, 2018)
EVCS lifetime	12	year	(Schroeder and Traber, 2012; Serradilla et al., 2017)
Delay time CS	3	year	(Schroeder and Traber, 2012; Serradilla et al., 2017)
Number of market party classes	2	Classes	*Self defined (See 4.1)*
Minimal investment rate	0.001	Dimensionless	(Olsina et al., 2006)
Commercial std max investment rate	2	Dimensionless	(Olsina et al., 2006)
NWC public incentive investment boost	*0 - 1*	*Dimensionless*	*Uncertainty range (See 4.6)*
Initial market share NWC	*0 - 100*	*%*	*Uncertainty range (See 4.6)*
Market entry period	*0 - 30*	*Year*	*Policy lever (See 4.7)*
No entry switch	*0,1*	*Binary switch*	*Policy lever (See 4.7)*
Market share cap	*0 - 100*	*%*	*Policy lever (See 4.7)*

B.2.2. Vehicle development structure constants & parameters

Table B.2: Constants with corresponding values, units, and literature references for the Vehicle development structure: General traffic development cycle. Uncertainty parameters shown in red.

Constant	Value	Units	Reference
Initial traffic [BEV]	762	Vehicles	(RVO, 2018)
Initial traffic [PHEV]	7103	Vehicles	(RVO, 2018)
Initial traffic [ICE]	7614478	Vehicles	(CBS, 2018b)
Initial traffic [Other]	10	Vehicles	(RVO, 2018)
Initial sales distribution [BEV]	0.1	%	(CBS, 2018a)
Initial sales distribution [PHEV]	1	%	(CBS, 2018a)
Initial sales distribution [ICE]	98,9	%	(CBS, 2018a)
Initial sales distribution [Other]	0	%	(CBS, 2018a)
Traffic growth factor	0.1776	%	(CBS, 2018b)
Traffic replacement factor	5.97	%	(RVO, 2018)
CS demand per vehicle	25	%	(Christensen et al., 2010; Kang and Recker, 2009; Weiller, 2011)

Table B.3: Constants with corresponding values, units, and literature references for the Vehicle development structure: Vehicle attractiveness structure. Uncertainty parameters shown in red.

Constant	Value	Units	Reference
Delay attractiveness effect	5	year	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter charging time	-0.0009	1/min	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter emissions	-0.0039	1/(g/km)	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter retail price	-0.0000456	1/€	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter range	0.0015	1/km	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter costs	-4.9	1/(€/km)	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Parameter facilities	0.0096	Dimensionless	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Error term base attractiveness [BEV]	-0.5	Dimensionless	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Error term base attractiveness [PHEV]	-0.712	Dimensionless	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Error term base attractiveness [ICE]	-0.113	Dimensionless	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Error term base attractiveness [Other]	-6	Dimensionless	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
ICE charging time	5	min	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Other charging time	5	min	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
CO2 emission per km [BEV]	0	g/km	(Ligterink et al., 2015)
CO2 emission per km [PHEV]	75	g/km	(Ligterink et al., 2015)
CO2 emission per km [ICE]	150	g/km	(Ligterink et al., 2015)
CO2 emission per km [Other]	0	g/km	*Self defined (See 4.3)*
Vehicle retail price [PHEV]	45000	€	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
Vehicle retail price [ICE]	28000	€	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
BEV RP initial	65000	€	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
BEV RP max shift	45000	€	*Reference value = ICE retail price*
BEV RP offset	2000	time	*Self defined (See 4.3)*
Range [PHEV]	704	km	(Halbey et al., 2017)
Range [ICE]	659,2	km	(Halbey et al., 2017)
Range [Other]	659,2	km	*Self defined (See 4.3)*
BEV R initial	100	km	(Hackbarth and Madlener, 2013; Jensen et al., 2013; Van den Brink and Annema, 2007)
BEV R max shift	700	km	*Self defined (See 4.3)*
BEV R offset	2000	time	*Self defined (See 4.3)*
Average fuel consumption [PHEV]	0.1	l/km	(Ligterink and Eijk, 2014)
Average fuel consumption [ICE]	0.05	l/km	(Ligterink and Eijk, 2014)
BEV FC initial	0.3	kWh/km	(Ligterink and Eijk, 2014)
BEV FC max shift	0.15	kWh/km	(Ligterink and Eijk, 2014)
BEV FC offset	2000	time	*Self defined (See 4.3)*
Other development initial	0	Dmnl	*Self defined (See 4.3)*
Alternative vehicle max attractiveness	*0 - 8*	*Dmnl*	*Uncertainty range (See 4.6)*
Alternative vehicle development speed	*0.05 - 0.35*	*Dmnl*	*Uncertainty range (See 4.6)*
Alternative vehicle technology introduction year	*2000 - 2030*	*time*	*Uncertainty range (See 4.6)*
BEV development speed	*0.1 - 0.2*	*Dmnl*	*Uncertainty range (See 4.6)*
ICE average fuel price	*0.80 - 1.60*	*€/l*	*Uncertainty range (See 4.6)*

B.2.3. EVCS returns structure constants & parameters

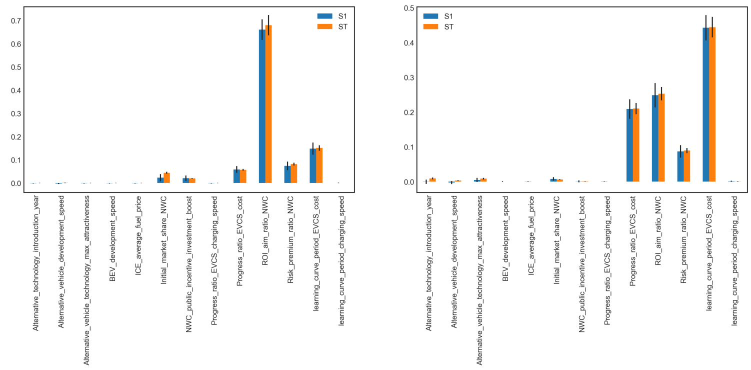
Table B.4: Constants with corresponding values, units, and literature references for the EVCS returns structure. Uncertainty parameters shown in red.

Constant	Value	Units	Reference
OPEX estimated back office running costs	400	€/year	(Serradilla et al., 2017)
OPEX annual DSO connection costs	1000	€/year	(Hop and Welleweerd, 2013)
CAPEX site costs	450	€	(Huisprijskompas, 2018; Serradilla et al., 2017)
CAPEX installation project management and operation	4500	€	(Serradilla et al., 2017)
CAPEX site preparation	10000	€	(Serradilla et al., 2017)
CAPEX new power connections	10000	€	(Hop and Welleweerd, 2013; Schroeder and Traber, 2012; Serradilla et al., 2017)
Average daily electricity consumption per BEV	6.15	kWh	(Serradilla et al., 2017)
Average public recharge rate	25	%	(Christensen et al., 2010; Kang and Recker, 2009; Weiller, 2011)
ROI aim	0.1	Dmnl	Self defined (See 4.4)
Time to adjust price	3	year	Self defined (See 4.4)
Initial charging fee	5	€	(Schroeder and Traber, 2012; Serradilla et al., 2017)
Risk premium C	4	%	(Eijgenraam et al., 2002)
Investment period	10	year	(Schroeder and Traber, 2012; Serradilla et al., 2017)
Initial marginal cost new EVCS	45000	€	(Schroeder and Traber, 2012; Serradilla et al., 2017)
Initial charging speed new EVCS	240	min	(Jensen et al., 2013; Schroeder and Traber, 2012; Serradilla et al., 2017; Van den Brink and Annema, 2007)
Learning curve period EVCS cost	*2 - 4*	*year*	*Uncertainty range (See 4.6*
Learning curve period charging speed	*2 - 4*	*year*	*Uncertainty range (See 4.6)*
Progress ratio EVCS cost	*0.5 - 0.7*	*Dmnl*	*Uncertainty range (See 4.6)*
Progress ratio EVCS charging speed	*0.3 - 0.5*	*Dmnl*	*Uncertainty range (See 4.6)*
ROI aim ratio NWC	*0 - 100*	*%*	*Uncertainty range (See 4.6)*
Risk premium ratio NWC	*0 - 100*	*%*	*Uncertainty range (See 4.6)*
Shareholder activation switch	*0,1*	*Binary switch*	*Policy lever (See 4.7)*

C

Base Case Analysis

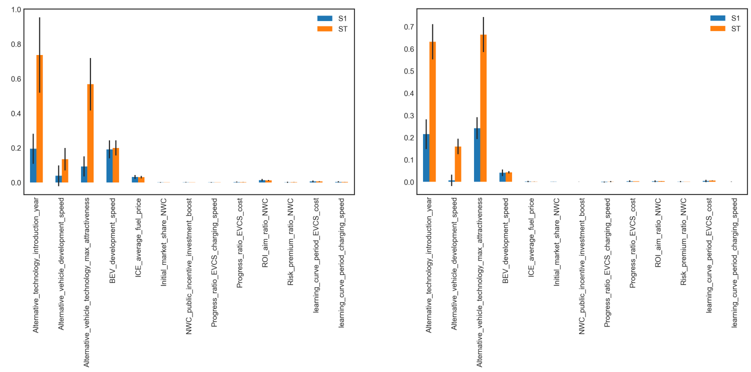
C.1. Sobol indices



(a) 2013 (b) 2015

Figure C.1: Barplots of Sobol analysis for **EVCS price per kWh** at no policy.

Figure 6.1.c shows two areas of interest: the large variation in the first period of 6 years, and the balanced period thereafter. 2013 as a mid-point in the first period and the end-state (2030) are selected for the sensitivity analysis. All ST confidence intervals of the prioritised factors that are mentioned earlier overlap with the $S1$ confidence intervals, showing that interaction effects are not significantly present.



(a) 2020 (b) 2030

Figure C.2: Barplots of Sobol analysis for **BEV sales share** at no policy.

Two moments have been selected for the sensitivity analysis: 2020 and 2030. As shown in figure 6.1.a, the outcomes start to diverge after 5 years, where a large variation is present from 2020 onwards and the largest variation is found at the end-state 2030, which is why these two moments have been selected for the sensitivity analysis. The significant interaction effects being present by the 3 alternative vehicle development parameters are examined further for second order effects.

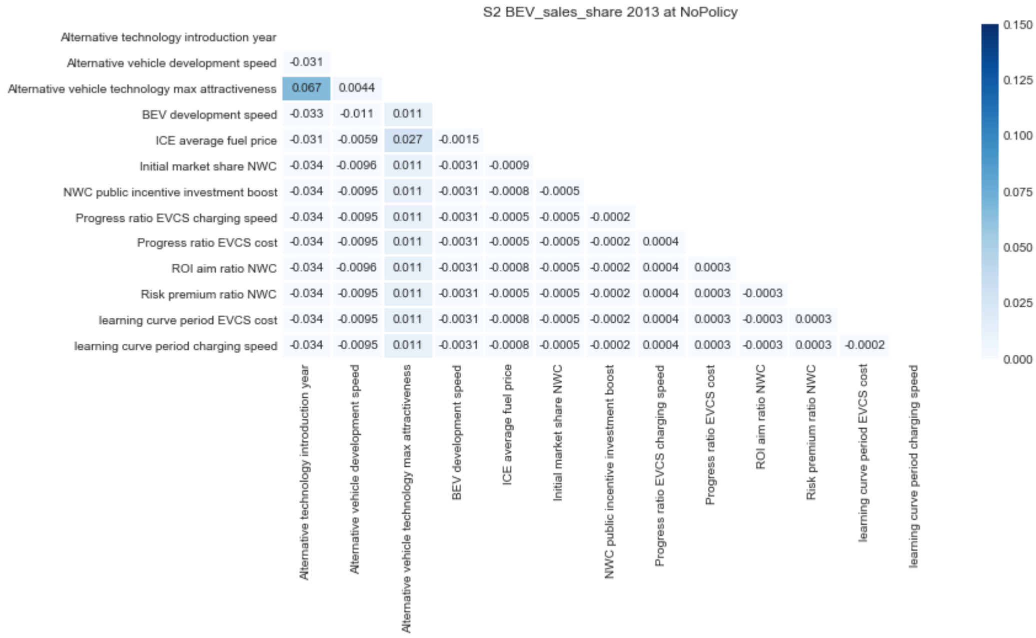


Figure C.3: Sobol second order effects of uncertainties on the BEV sales share in 2013. Columns and rows indicate uncertainties and their interactions.

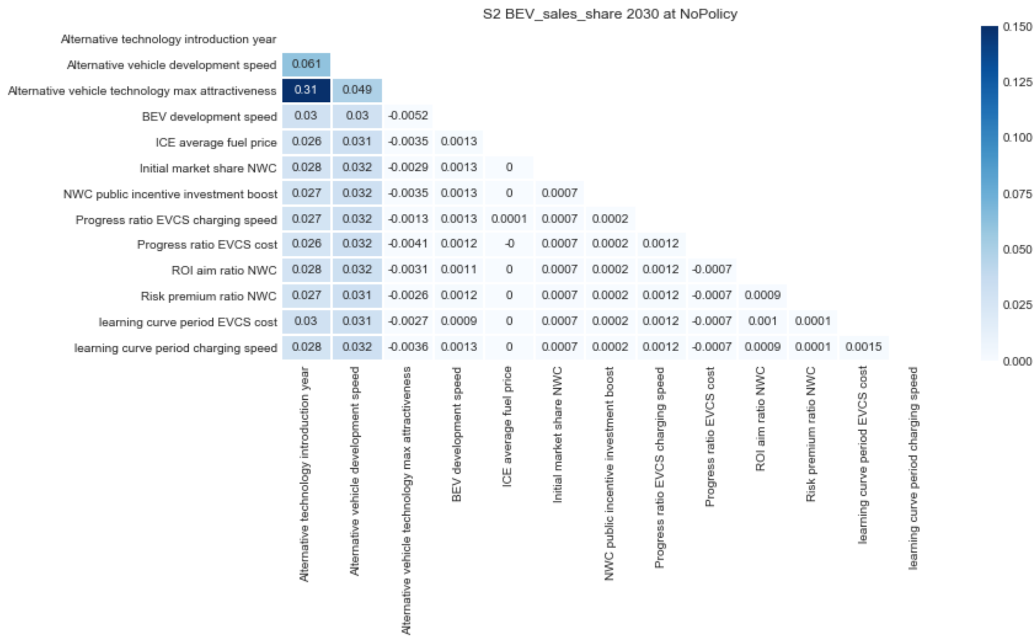
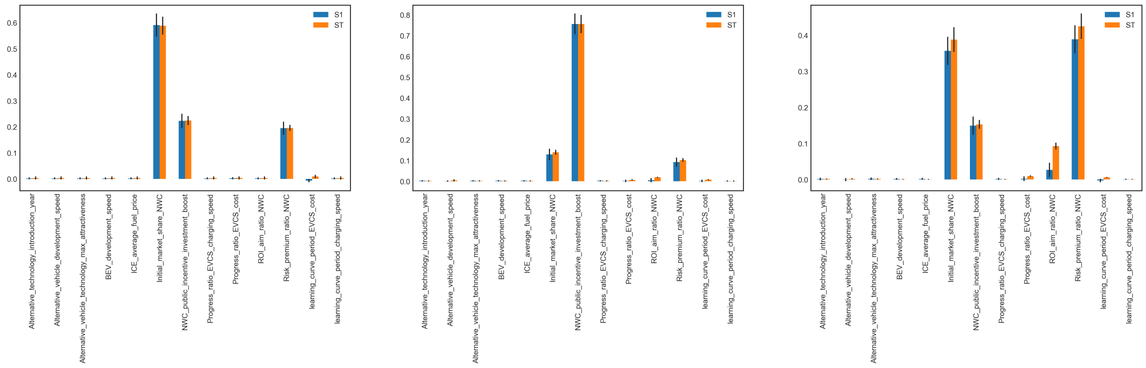


Figure C.4: Sobol second order effects of uncertainties on the BEV sales share in 2030. Columns and rows indicate uncertainties and their interactions.

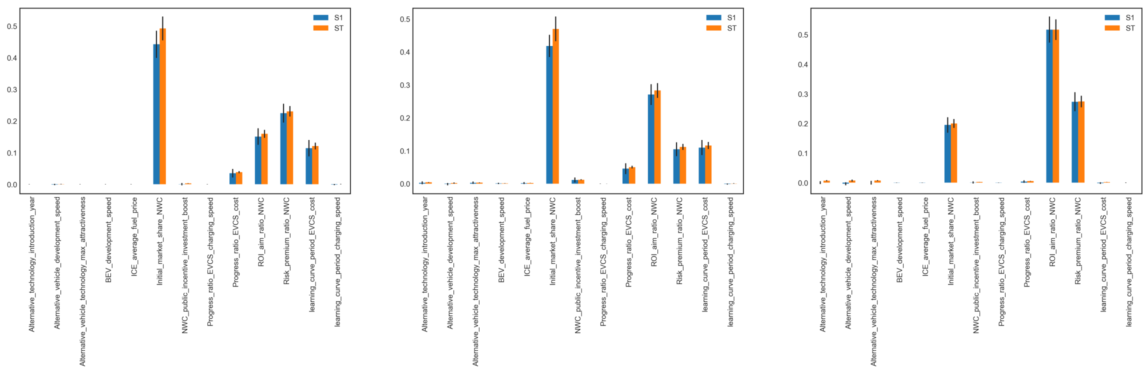
The NWC market share initials are determined by the input settings of the direct initial, but figure 6.1.e shows an interesting tipping point around 2015 where outcomes not only converge but seem to crossover from high to low values compared to the mean or vice versa. The moments of interest are therefore just before and just after the tipping point at 2015, and the end state: 2013, 2017, and 2030. Confidence intervals overlap here,



(a) 2013 (b) 2017 (b) 2030

Figure C.5: Barplots of Sobol analysis for **Market share NWC** at no policy.

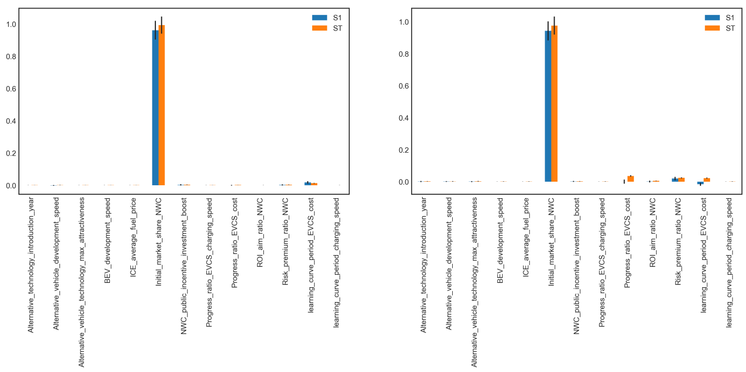
meaning there are no significant interaction effects present.



(a) 2012 (b) 2014 (b) 2030

Figure C.6: Barplots of Sobol analysis for **ROI Commercial** at no policy.

From the ROI commercial development shown in figure 6.1.f, 3 different moments can be distinguished: a strong descend with its minima in 2012, a strong ascend with its peaks in 2014, and the balanced period after 2020. The the first two points are selected, and for the balanced final phase the end-state is chosen again.

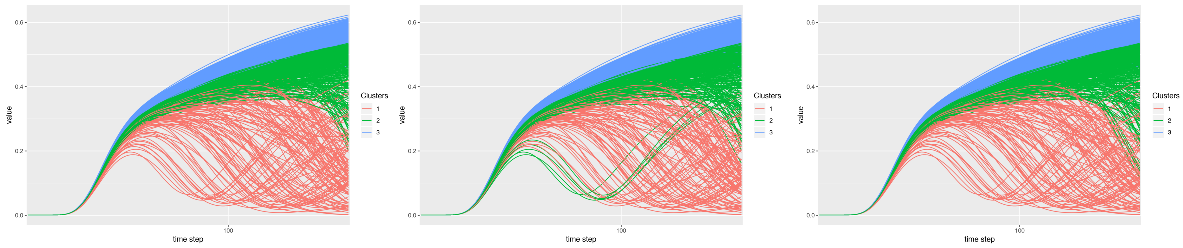


(a) 2013 (b) 2030

Figure C.7: Barplots of Sobol analysis for **CAPEX gap** at no policy.

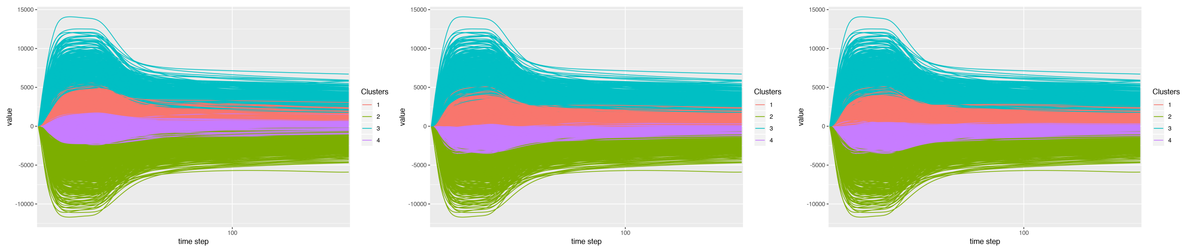
The sensitivity analysis for the CAPEX gap is targeted at two stages of the graph shown in figure 6.1.c: the strong short-term divergence of the outcome ensemble in the first period that converges again towards 2016, and the balanced second part after it until 2030. The selected moments are therefore the mid point of the first period: 2013, and the end-state 2030. The main effect index $S1$ is nearly 1 and its total effect's (ST) confidence interval overlaps with the confidence interval of $S1$, also ruling out significant interaction effects.

C.2. Clustering methods comparison



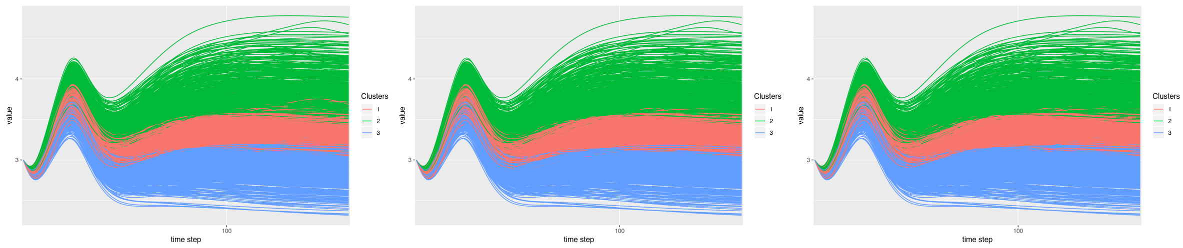
(a) CID (b) CORT (c) DWT

Figure C.8: BEV sales share outcomes for different clustering methods with k=3.



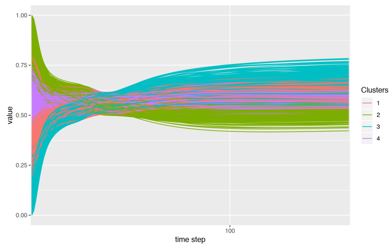
(a) CID (b) CORT (c) DWT

Figure C.9: CAPEX gap outcomes for different clustering methods with k=4.

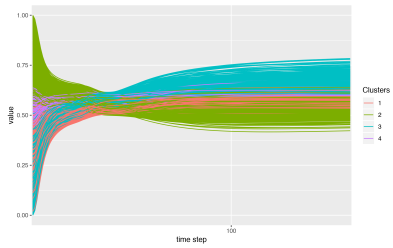


(a) CID (b) CORT (c) DWT

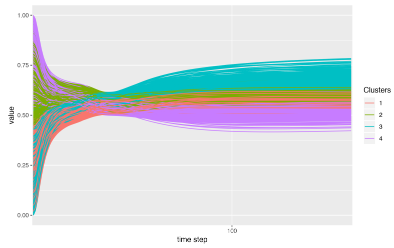
Figure C.10: EVCS price per kWh outcomes for different clustering methods with k=3.



(a) CID

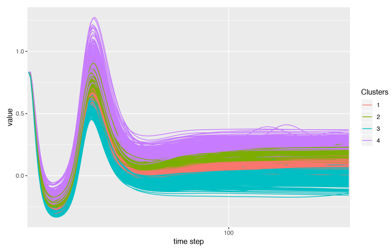


(b) CORT

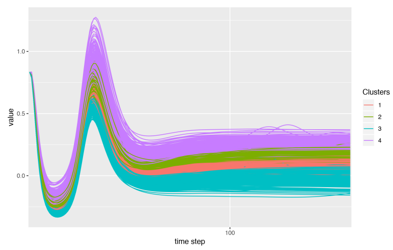


(c) DWT

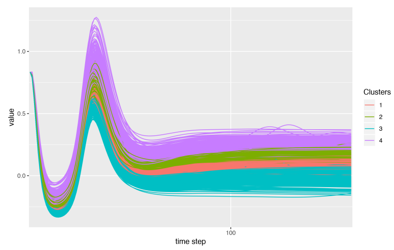
Figure C.11: Market share NWC outcomes for different clustering methods with k=4.



(a) CID



(b) CORT



(c) DWT

Figure C.12: ROI Commercial outcomes for different clustering methods with k=4.

C.3. Time Series Clustering: Complete pairs plots

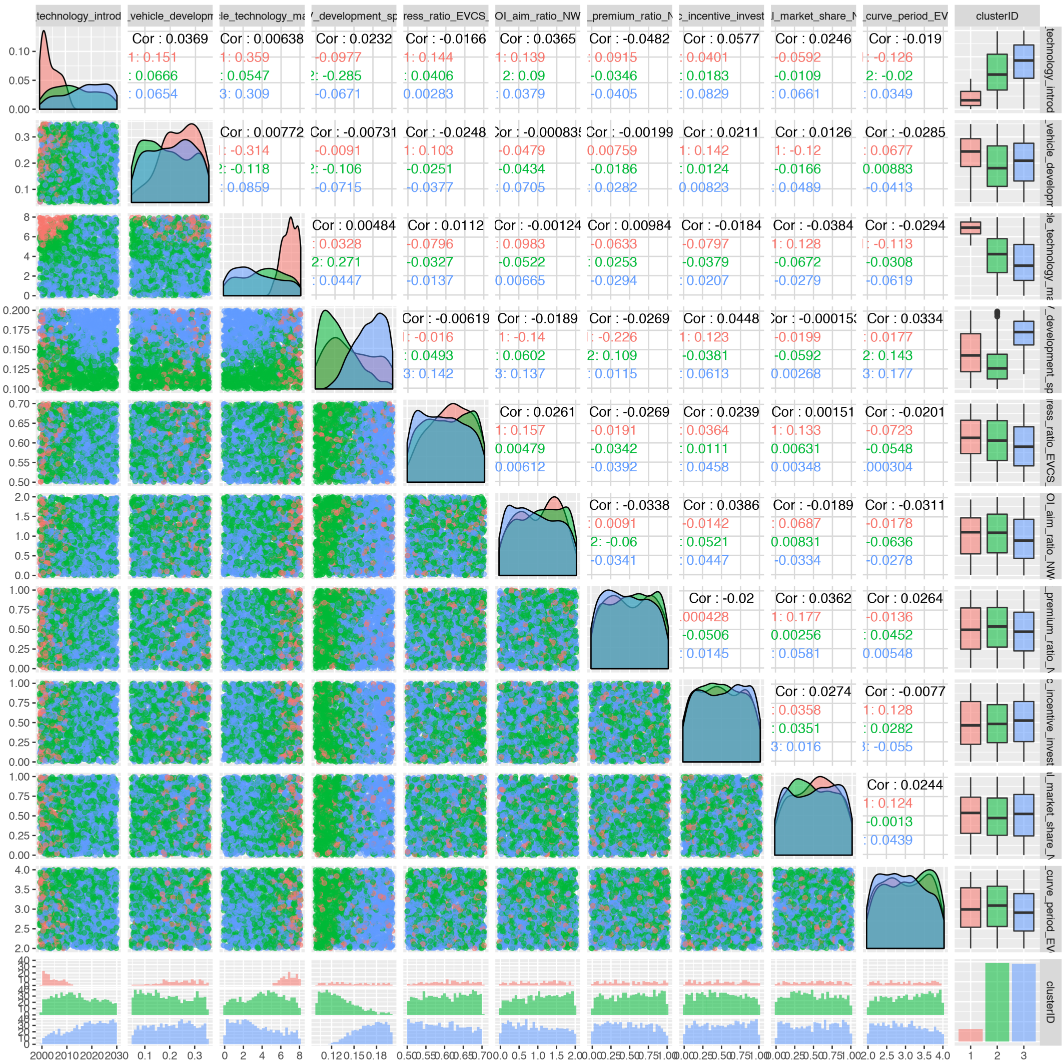


Figure C.13: Complete pairsplot of BEV sales share at no policy.

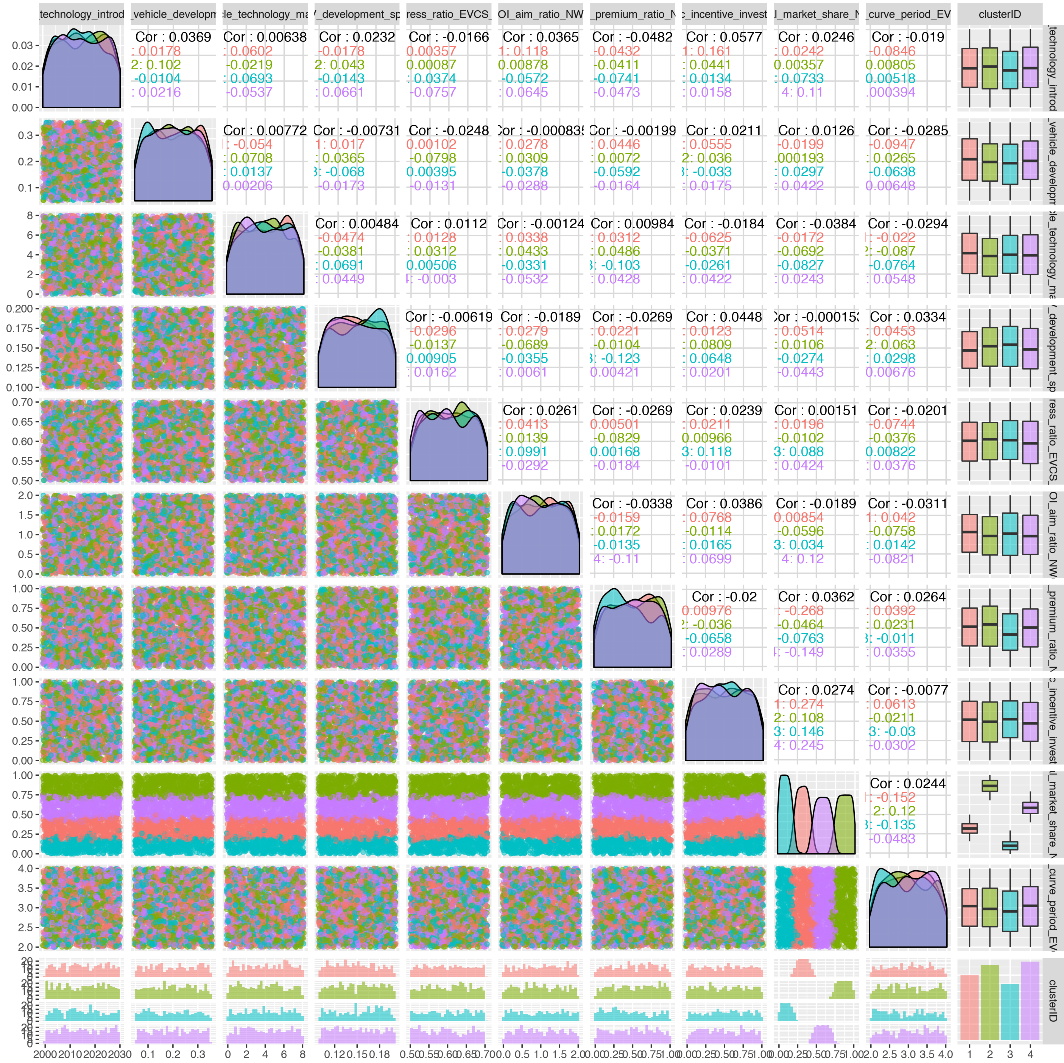


Figure C.14: Complete pairsplot of CAPEX gap at no policy.

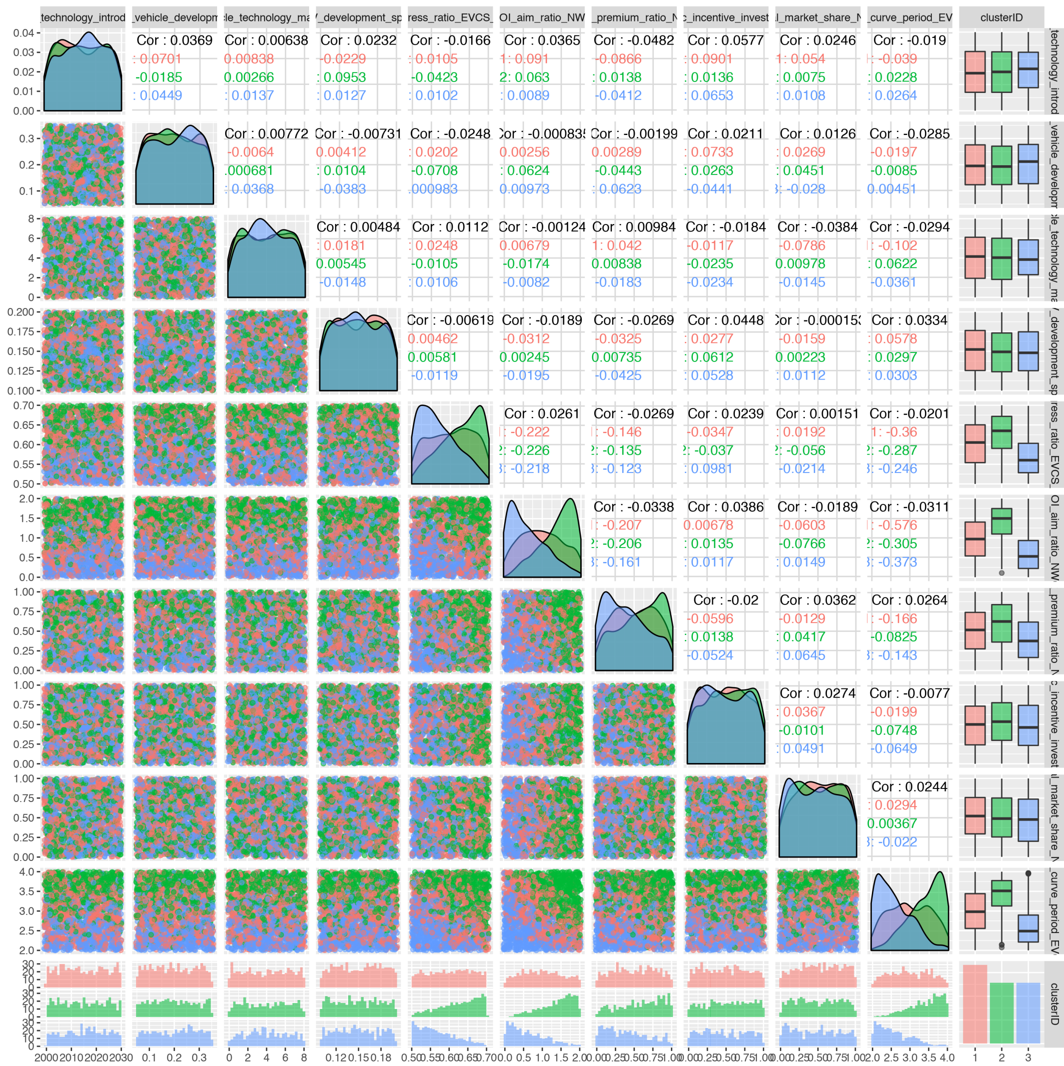


Figure C.15: Complete pairsplot of EVCS price per kWh at no policy.

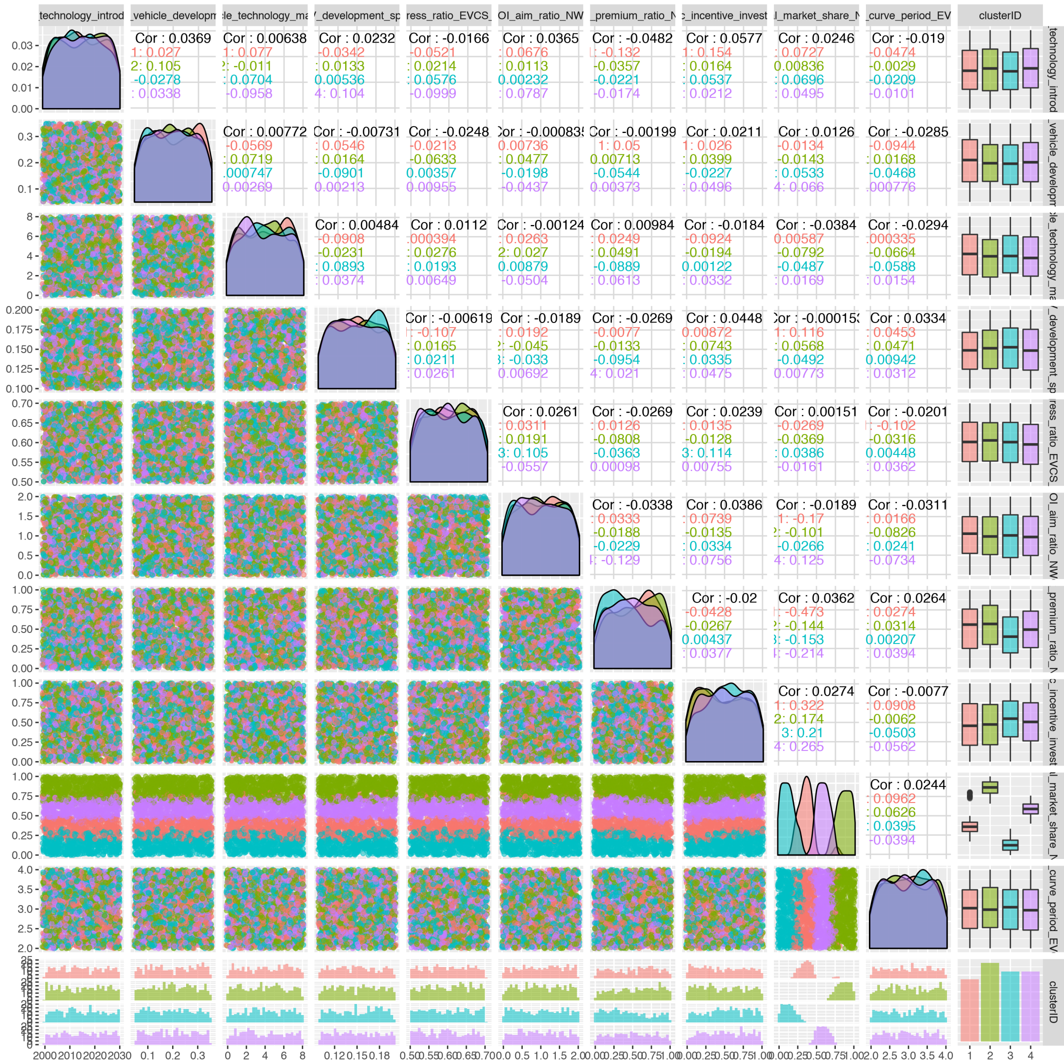


Figure C.16: Complete pairsplot of Market share NWC at no policy.

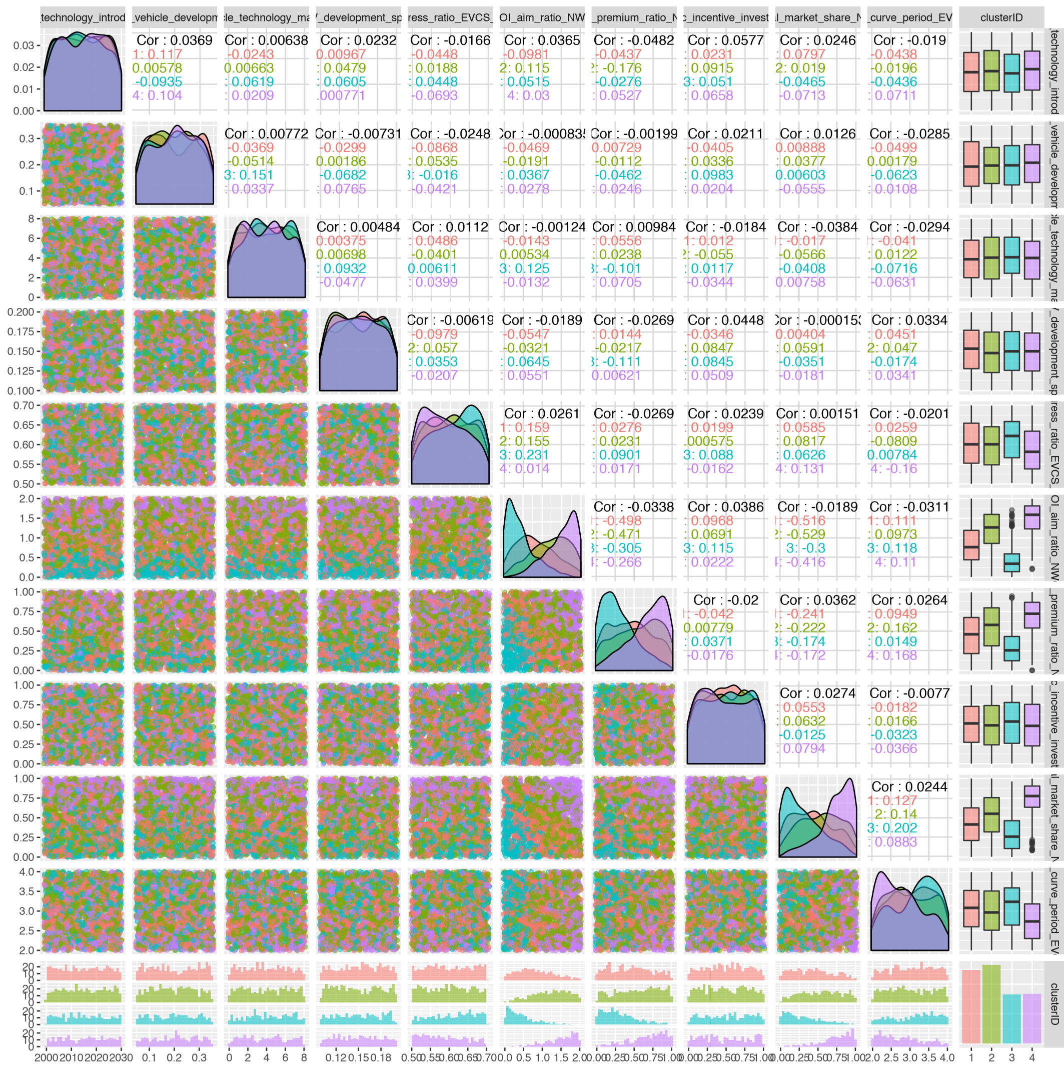
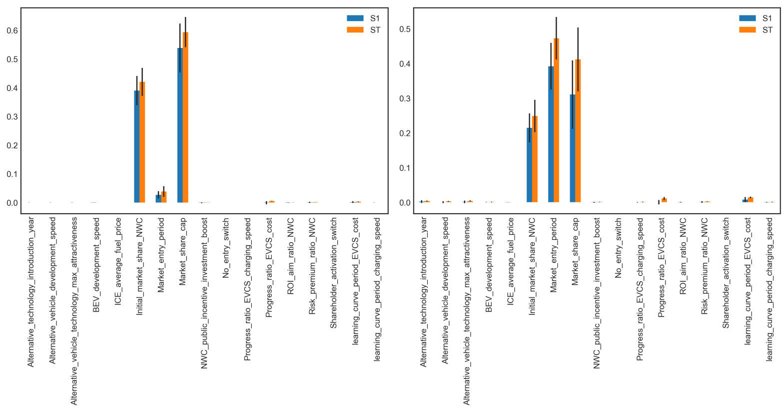


Figure C.17: Complete pairsplot of ROI commercial at no policy.

D
Policy Analysis

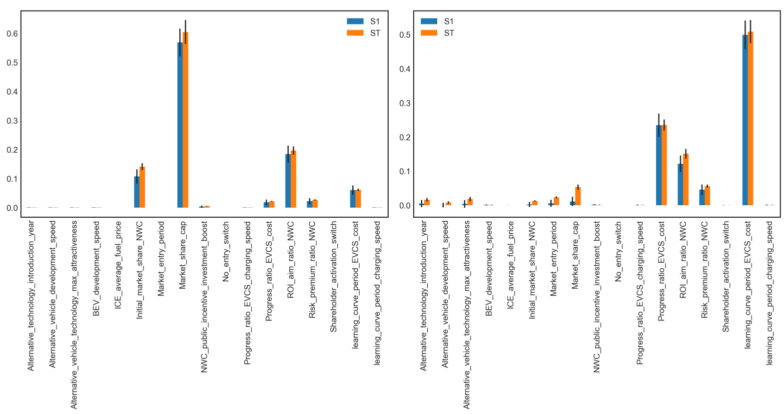
D.1. Sobol indices



(a) 2018 (b) 2030

Figure D.1: Barplots of Sobol analysis for **CAPEX gap** at mixed policies.

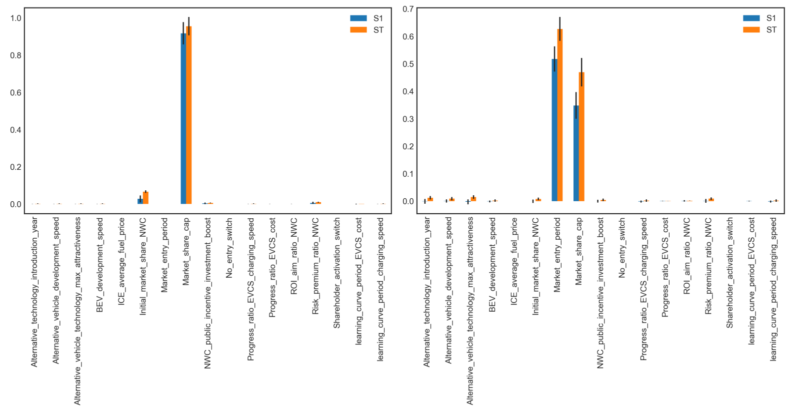
For the CAPEX gap, the moments of interest have been selected by taking both the end-state and the divergence point at 2018. The parameters do show some interaction effects: the complete confidence intervals of the total effect of both policy parameters are higher than the mean values of the main effects, but still overlap with the main effect confidence intervals.



(a) 2013 (b) 2025

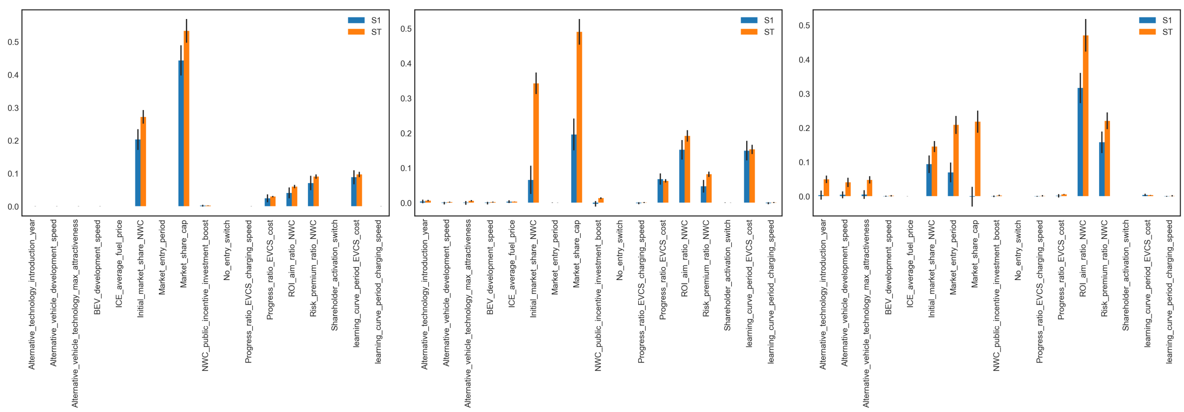
Figure D.2: Barplots of Sobol analysis for **EVCS price per kWh** at mixed policies.

The interesting points of interest of the EVCS price are found at the high peak at 2013 and the 2025 moment which contains several outliers.



(a) 2013 (b) 2030

Figure D.3: Barplots of SOBOL analysis for **Market share NWC** at mixed policies.



(a) 2012 (b) 2014 (c) 2030

Figure D.4: Barplots of SOBOL analysis for **ROI Commercial** at mixed policies.

Several points in time have been selected for ROI commercial based on the visual assessment of the behaviour. Significant interaction effects are observed here: many confidence intervals for ST lie higher than the $S1$ confidence intervals. $S2$ indices are presented in the following figures.

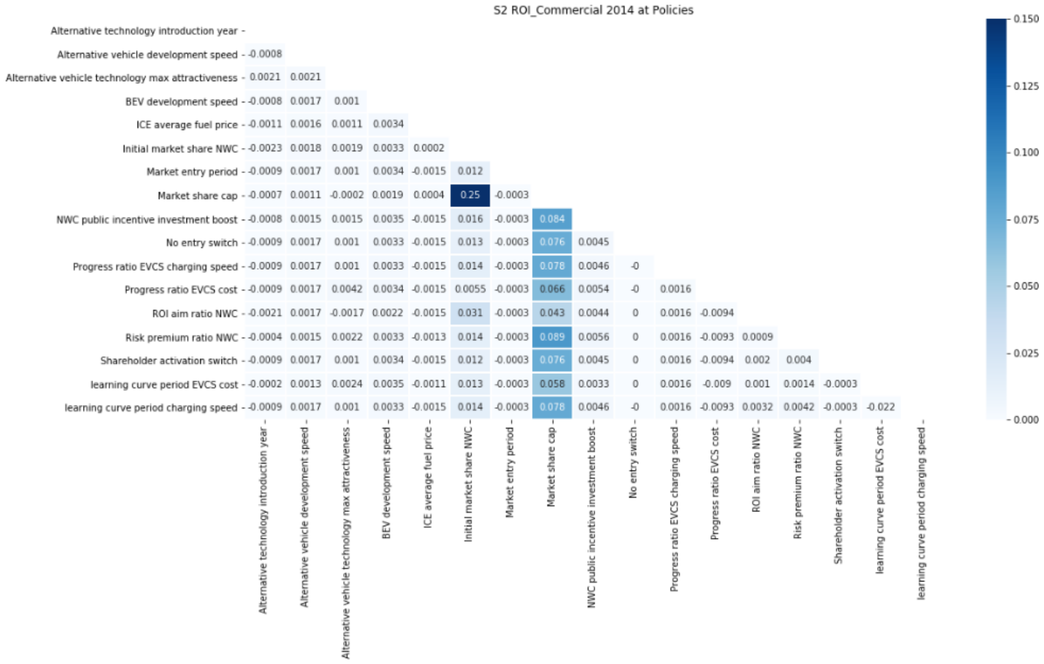


Figure D.5: Sobol second order effects of uncertainties on the ROI Commercial in 2013. Columns and rows indicate uncertainties and their interactions.

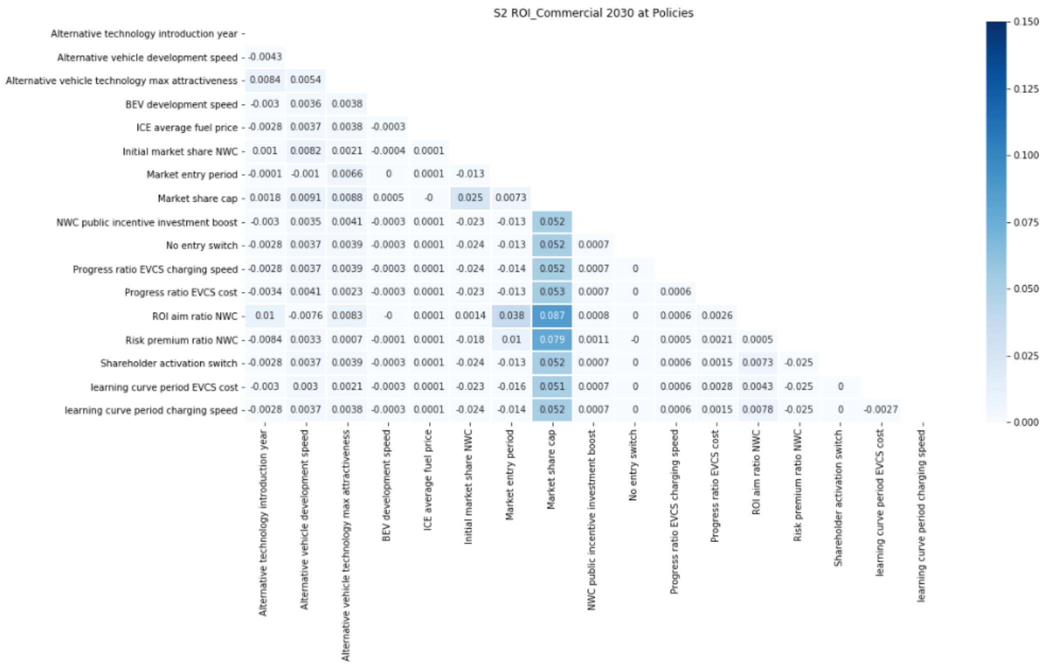
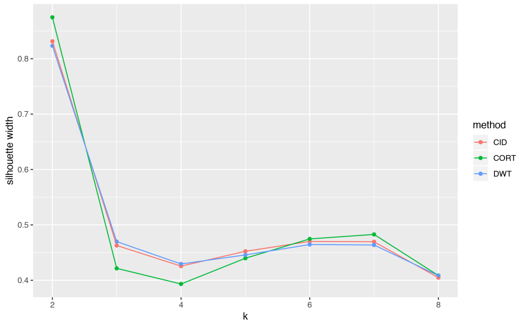


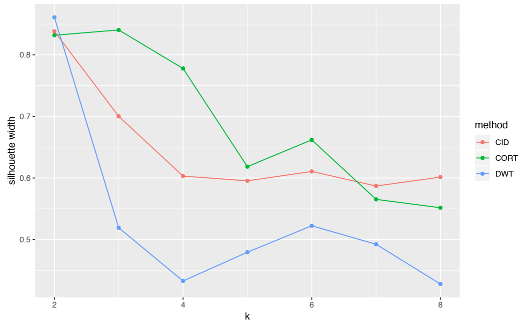
Figure D.6: Sobol second order effects of uncertainties on the ROI Commercial in 2030. Columns and rows indicate uncertainties and their interactions.

D.2. Time Series Clustering: Defined policies

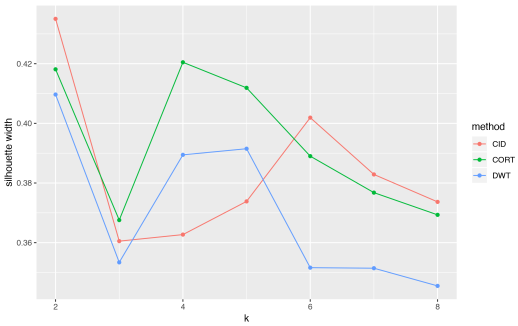
D.2.1. Cluster counts



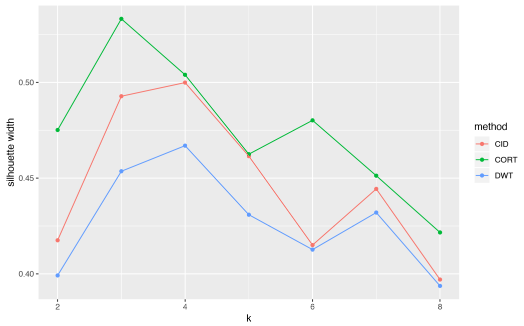
(a) BEV sales share



(b) CAPEX gap



(c) EVCS charging price

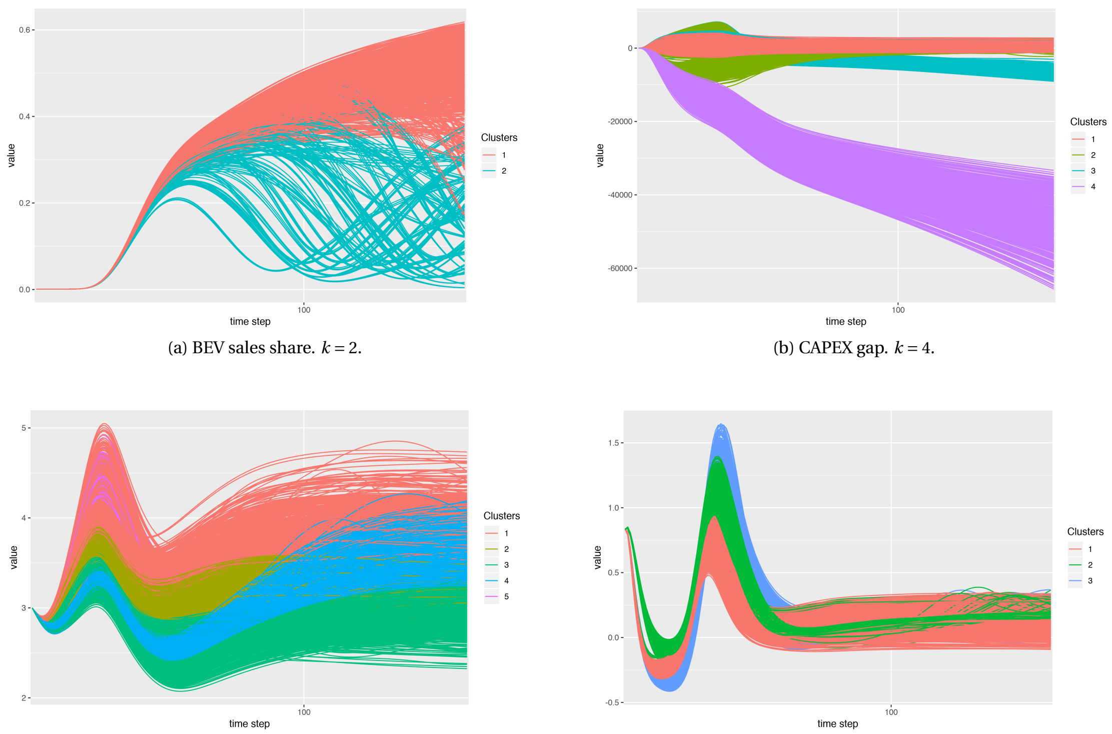


(e) ROI Commercial

Figure D.7: Silhouette widths of CID-, CORT- and DWT-generated cluster counts with k = amount of clusters at defined policies.

BEV sales share shows by far the highest value at k=2. Since the model analysis showed that the two higher clusters are explained by a majority of similar input parameters, this time the highest silhouette value will be used and a cluster count of 2 will be maintained. The CAPEX gap silhouette widths vary more across different methods. CORT validity increases slightly when going higher, other method's silhouette widths decrease when higher than k=2, and higher values still show stable and high silhouette widths. Because of the asymmetry now of the ensemble in figure 6.3.b, the cluster count for CAPEX gap was initially fixed at k=3, but after one clustering process it became clear that one cluster consisted of two different parts with similar behaviour, but still desirable to be separated. Therefore the CAPEX gap cluster count is set to k=4. EVCS price per kWh is settled at k=5, for it also has a relatively large combined silhouette width and the values are converged at that point. Market share NWC is a very complicated comparison, however, by using figure 6.5.b, 5 is selected visually. ROI commercial has its highest combined silhouette width at k=3, which shall be used for this outcome.

D.2.2. Clustered line-plots



(a) BEV sales share. $k = 2$.

(b) CAPEX gap. $k = 4$.

(c) EVCS charging price. $k = 5$.

(e) ROI Commercial. $k = 3$

Figure D.8: Clustered line-plots of CID-, CORT- and DWT-generated cluster counts with k = amount of clusters at mixed policies.

D.2.3. Complete pairs plots

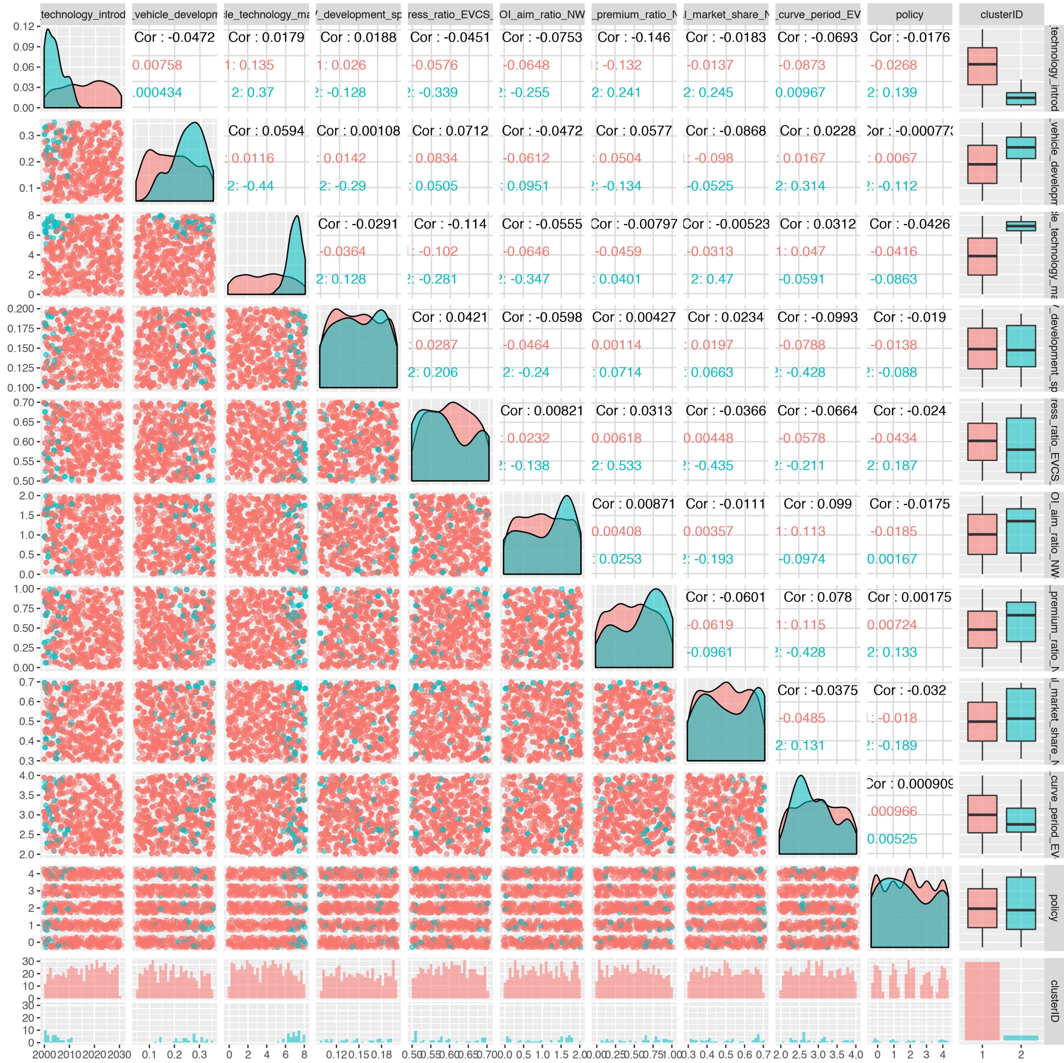


Figure D.9: Complete pairsplot of BEV sales share at defined policies.

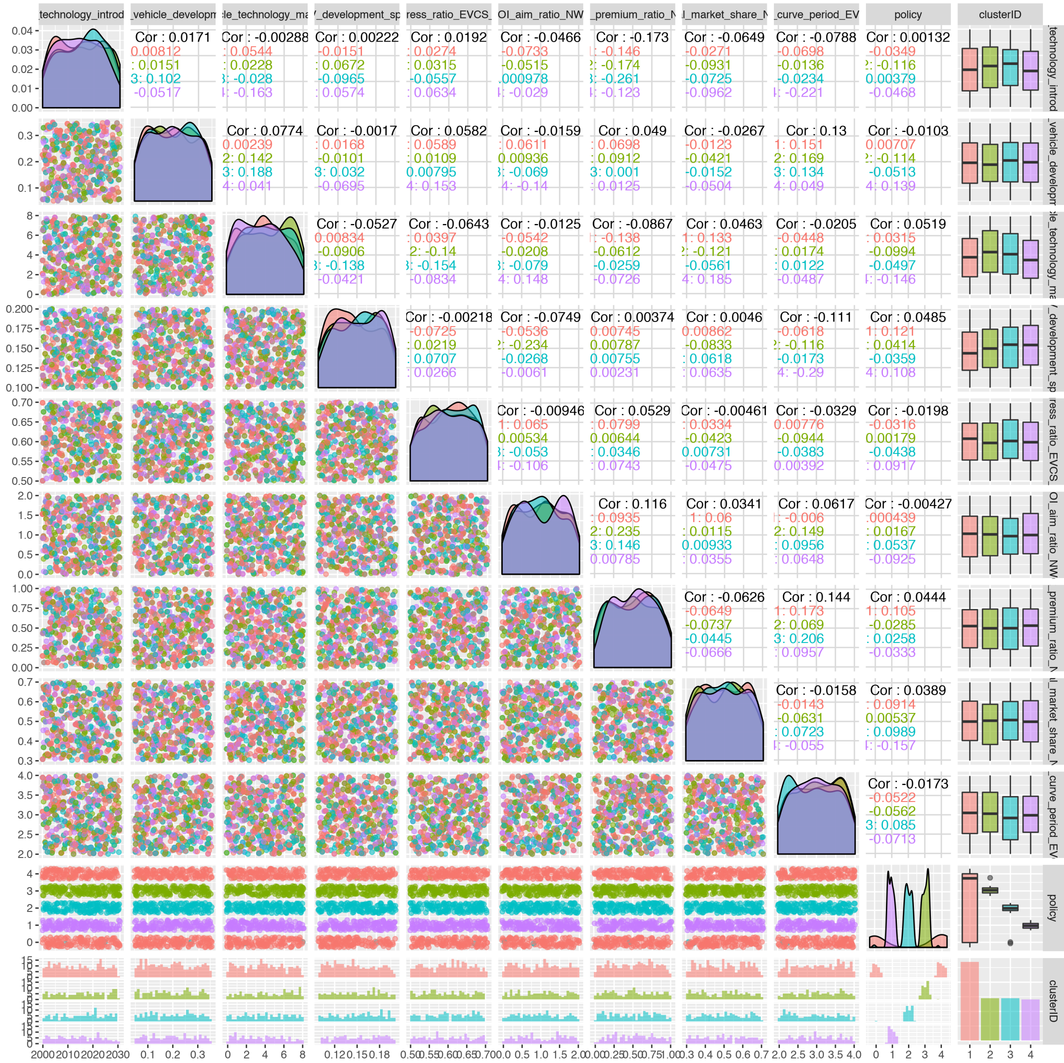


Figure D.10: Complete pairsplot of CAPEX gap at defined policies.

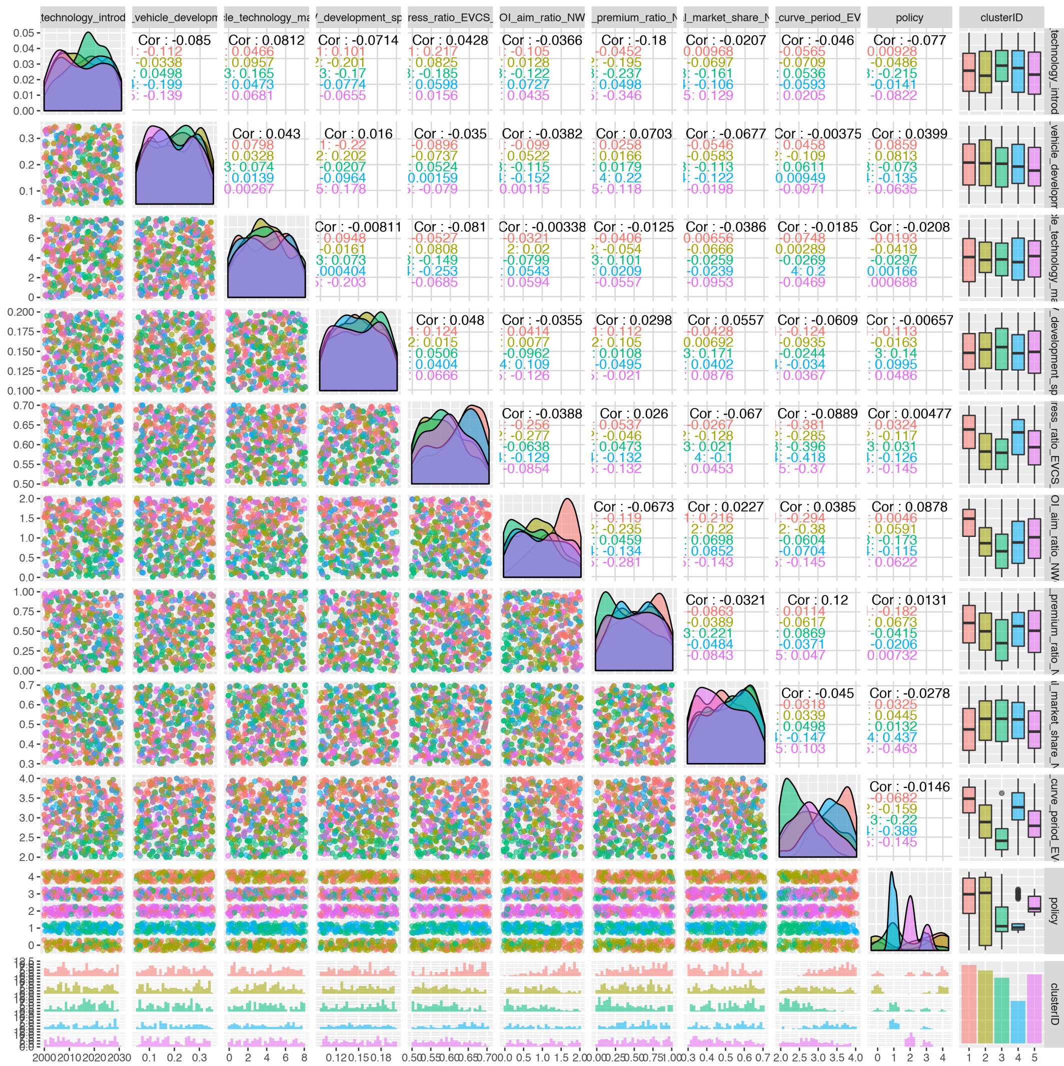


Figure D.11: Complete pairsplot of EVCS charging price per kWh at defined policies.

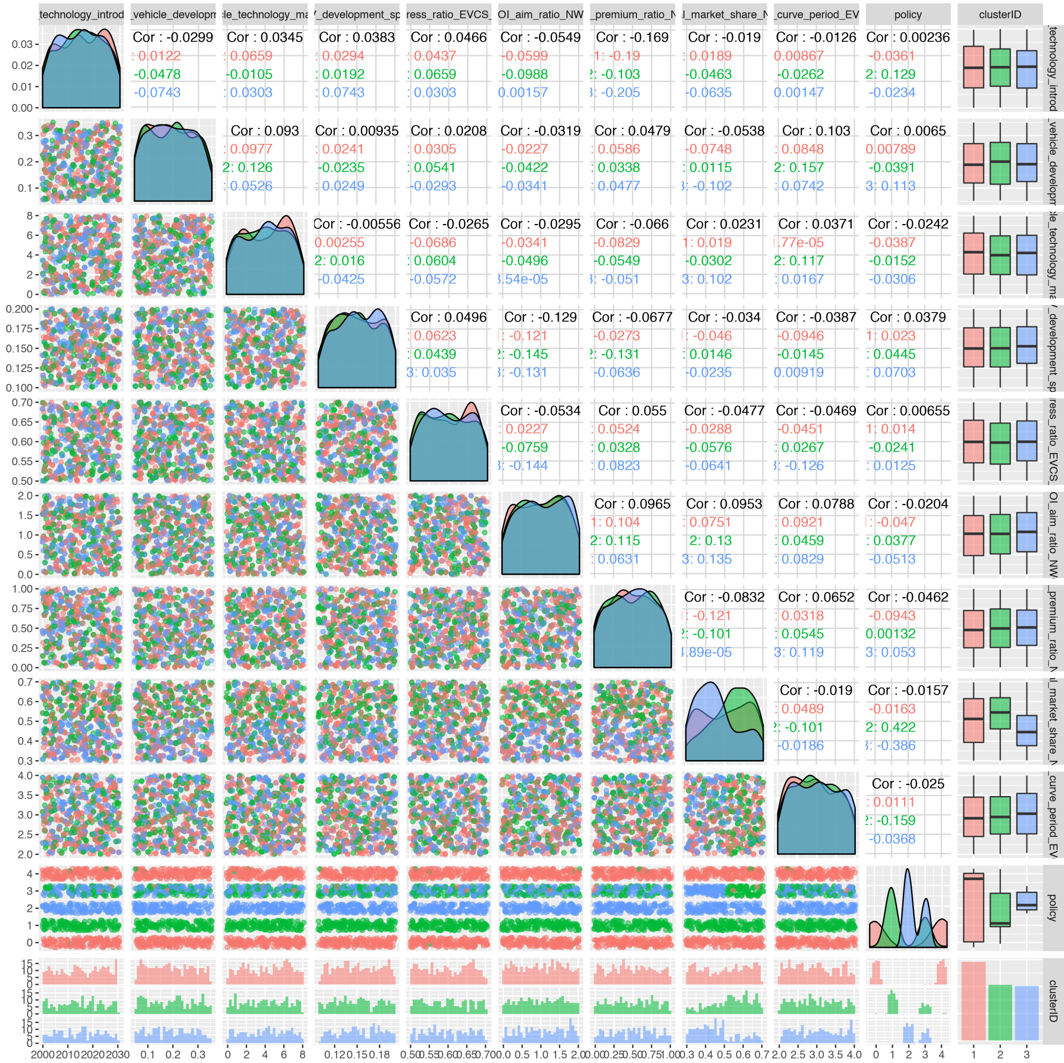
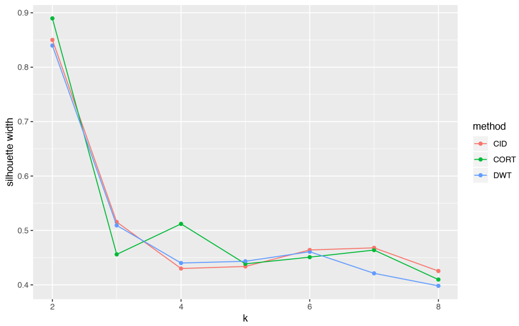


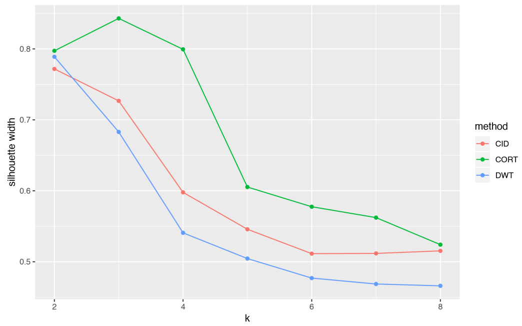
Figure D.12: Complete pairsplot of ROI commercial at defined policies.

D.3. Time Series Clustering: Mixed policies

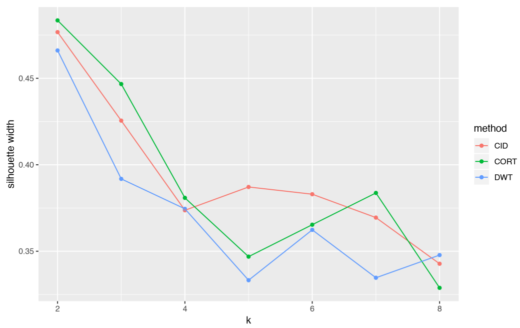
D.3.1. Cluster counts



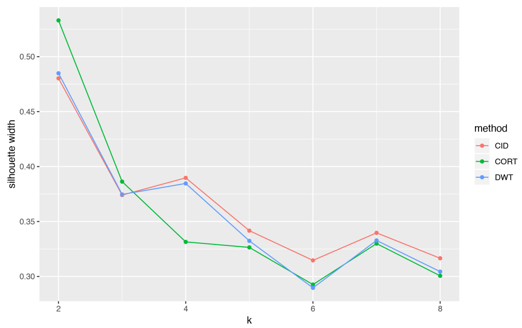
(a) BEV sales share



(b) CAPEX gap



(c) EVCS charging price

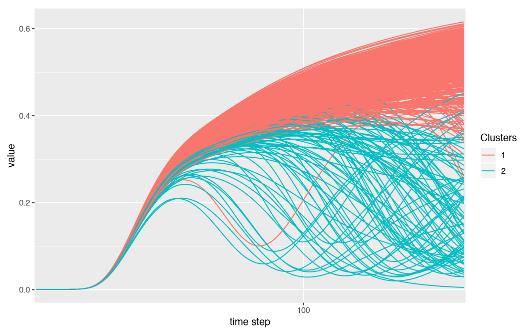


(e) ROI Commercial

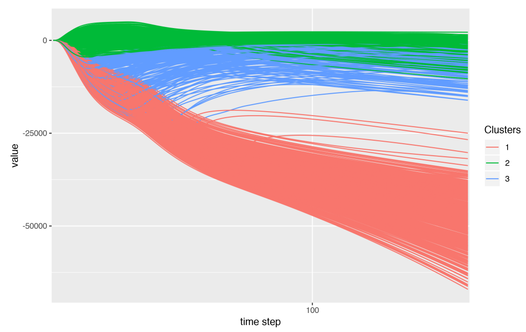
Figure D.13: Silhouette widths of CID-, CORT- and DWT-generated cluster counts with k = amount of clusters at mixed policies.

BEV sales share shows by far the highest value at k=2 again. Since the model analysis showed that the two higher clusters are explained by a majority of similar input parameters, this time the highest silhouette value will be used and a cluster count of 2 will be maintained, similar to defined policies. Because of the asymmetry now of the ensemble in figure 6.3.b combined with the fact that sum of all silhouette widths is highest at 3, the cluster count for CAPEX gap was initially fixed at k=3, but after one clustering process it became clear that one cluster consisted of two different parts with similar behaviour, but still desirable to be separated. Therefore the CAPEX gap cluster count is set to k=4. EVCS price per kWh is settled at k=3, for it also has a relatively large combined silhouette width and the values are converged at that point and 3 will provide slightly more insights than 2. ROI commercial has by far its highest combined silhouette width at k=2, which shall be used for this outcome.

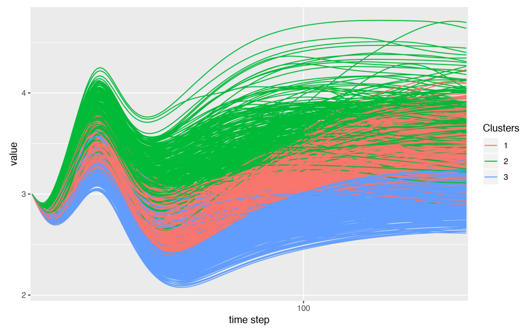
D.3.2. Clustered line-plots



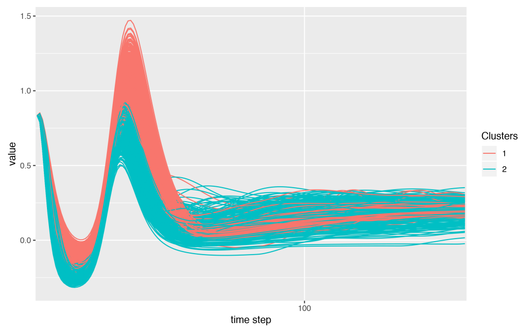
(a) BEV sales share. $k = 2$.



(b) CAPEX gap. $k = 3$.



(c) EVCS charging price. $k = 3$.



(e) ROI Commercial. $k = 2$.

Figure D.14: Clustered line-plots of CID-, CORT- and DWT-generated cluster counts with k = amount of clusters at mixed policies.

D.3.3. Complete pairs plots

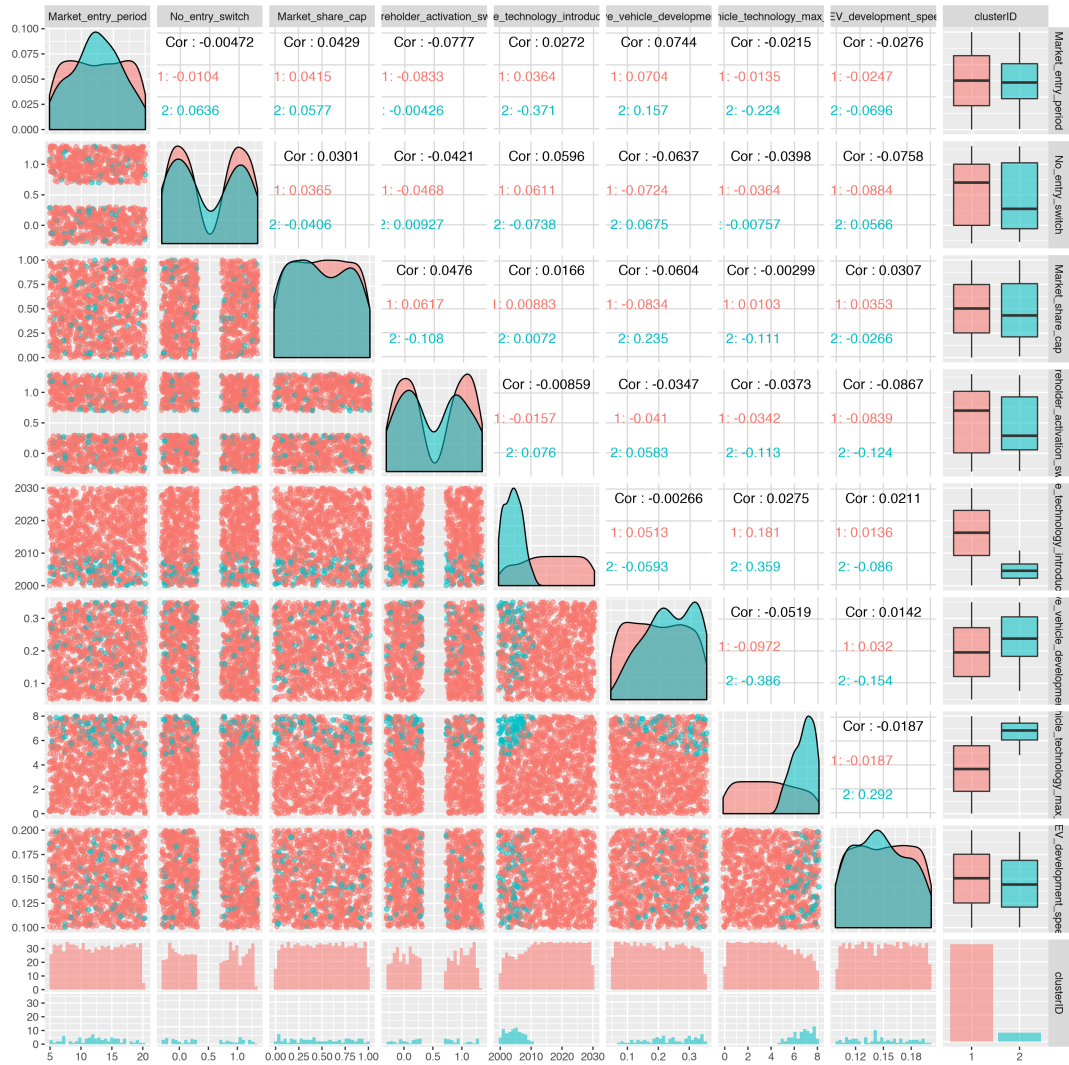


Figure D.15: Complete pairsplot of BEV sales share at mixed policies.

Figure D.16: Complete pairsplot of CAPEX gap at mixed policies.

Figure D.17: Complete pairsplot of EVCS charging price per kWh at mixed policies.

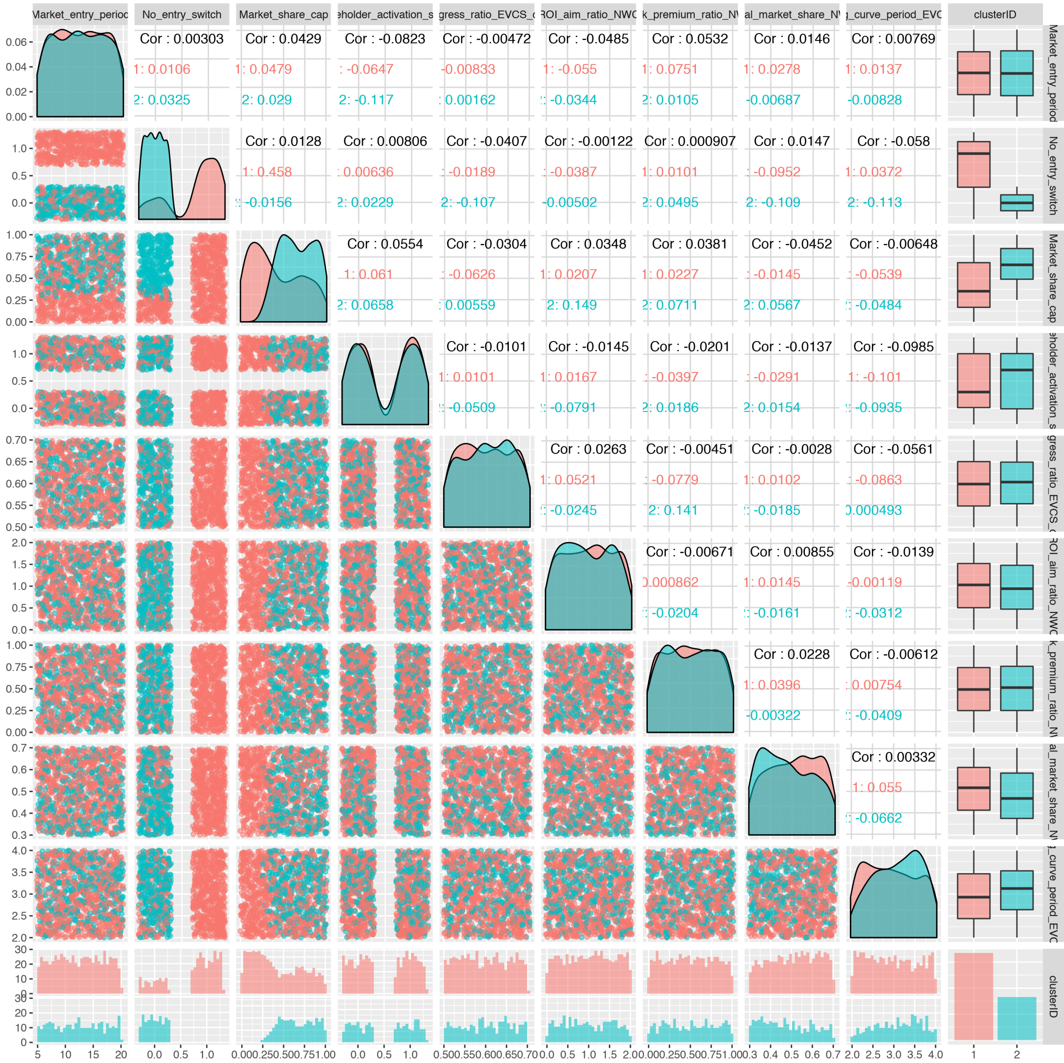


Figure D.18: Complete pairsplot of ROI commercial at mixed policies.

E
Python Scripts

The Python scripts for the experimentation, the exploration, and the sensitivity analysis are added here.

1 - No policy experiments setup and export

November 19, 2018

```
In [ ]: import numpy as np
        import pandas as pd
        import os
        import feather
        import datetime
        import seaborn as sns

        from ema_workbench import (Model,
                                   RealParameter,
                                   IntegerParameter,
                                   Constant,
                                   TimeSeriesOutcome,
                                   perform_experiments,
                                   ema_logging,
                                   save_results,
                                   perform_experiments,
                                   ema_logging,
                                  load_results)

        from ema_workbench.connectors.vensim import VensimModel

        import ema_workbench.analysis.pairs_plotting as pairs
        import ema_workbench.analysis.plotting as emaplt
        from ema_workbench.analysis.plotting import lines
        from ema_workbench.analysis.plotting_util import KDE

        import matplotlib.pyplot as plt

        # turn on logging
        ema_logging.log_to_stderr(ema_logging.INFO)
```

```
In [ ]: # Function to easily save all outcomes of interest
        def export_outcomes(outcomes, location = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analys
            """takes EMA outcomes and exports all time series for each outcome of interest as
            import into R. Arguments: export_outcomes(name of EMA outcomes dict, desired save
            defaults to './Data/'.
```

```
    """

    today = datetime.date.today()
    datestr = (str(today))

    keylist = list(outcomes.keys())

    for k in keylist:
        df_temp = pd.DataFrame(outcomes[k])
        df_temp = df_temp.copy()
        path = location + datestr + k.replace(' ','') + '.feather'
        feather.write_dataframe(df_temp,path)

    return("Done.");

# Function for creating line plots with density maps for observed interests
def plot_interests(interests, label, experiments_to_show, save):
    prefix = str(label)
    for kpi in interests:
        fig, axes = lines(results, outcomes_to_show=kpi,density=KDE,experiments_to_sho
        if save == 'y':
            plt.savefig('{}/fig_{}_highres.png'.format("Z:\stack\Documenten\TU\EPA\MSc_
        else:
            print(str(kpi)+'figure not saved')
    plt.show()
```

1 No policy

First, the model must be loaded and parameters should be set.

In [ ]:
```
# Load basic model for scenario discovery
wd = r''
model = VensimModel("NoPolicy", wd=wd, model_file='Model\Modelv9NoPolicy.vpm')
```

In [ ]:
```
# Define experiment parameters

# Define uncertainty ranges
uncertainties = [
                RealParameter("Alternative_technology_introduction_year",2000,2030), #
                RealParameter("Alternative_vehicle_technology_max_attractiveness",0,8)
                RealParameter("Alternative_vehicle_development_speed",0.05,0.35),
                RealParameter("BEV_development_speed",0.1,0.2),
                RealParameter("Risk_premium_ratio_NWC",0,1),
                RealParameter("ICE_average_fuel_price",0.80,1.60),
                RealParameter("ROI_aim_ratio_NWC",0,2),
                RealParameter("NWC_public_incentive_investment_boost",0,1),
                RealParameter("Initial_market_share_NWC", 0,1),
                RealParameter("learning_curve_period_EVCS_cost",2,4),
```

```
                RealParameter("learning_curve_period_charging_speed",2,4),
                RealParameter("Progress_ratio_EVCS_cost",0.5,0.7),
                RealParameter("Progress_ratio_EVCS_charging_speed",0.3,0.5)
                ]

# Formulate outcomes of interest
outcomes =  [
                TimeSeriesOutcome("EVCS_price_per_kWh"), #
                TimeSeriesOutcome("BEV_sales_share"),
                TimeSeriesOutcome("Market_share_semi_public"),
                TimeSeriesOutcome("ROI_Commercial"),
                TimeSeriesOutcome("CAPEX_gap"),
                TimeSeriesOutcome("EVCS_per_BEV")
            ]

# Override some of the constants in the model for quick access
constants = [
                Constant("Initial_active_EVCS", 200), # Initial amount of active EVCS
                Constant("Initial_EVCS_in_preparation",200), # Initial amount of EVCS
                Constant("time_to_adjust_price",3), # Time delay of market price avera
                Constant("Delay_attractiveness_effect",5),
                Constant("ROI_aim",0.2),
                Constant("Initial_charging_fee",3)
    # to do: add OPEX and CAPEX constants
            ]
```

In [ ]:
```
# Assign model settings
model.uncertainties = uncertainties
model.outcomes = outcomes
model.constants = constants

# Perform experiments
nr_experiments = 1000
results = perform_experiments(model, nr_experiments)

experiments, outcomes = results
```

In [ ]:
```
save_results(results, 'Data/NoPolicy_1000scenarios.tar.gz')
```

2 Outcome exploration

In [ ]:
```
# load data
data = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/NoPolicy_1000scenarios.tar
results = load_results(data)

experiments, outcomes = results
nr_experiments = 1690
```

```
In [ ]: # Plot result overview
        figure = emaplt.lines(results,density=u'kde')
        plt.show() #show figure

In [ ]: interests = ["EVCS_price_per_kWh"]#,"BEV_sales_share","Market_share_semi_public","ROI_

In [ ]: nr_experiments = 1000

In [ ]: plot_interests(interests, 'NoPolicy', 1000, 'y')
```

3 Data export

```
In [ ]: # Export all outcomes
        export_outcomes(outcomes)

In [ ]: # Exporting experiments data
        filelabel = "Nopolicy"
        df_expt = pd.DataFrame(experiments) #create dataframe from experiments (array of tuple
        for i, row in df_expt.iterrows():
            df_expt.set_value(i,'policy',0) #otherwise float error at no policies
        df_expt2 = df_expt.iloc[:,0:-1].astype("float")
        df_expt2 = df_expt2.copy() #self-copy to prevent errors
        path = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/" + filelabel + "_" + str(
        feather.write_dataframe(df_expt2,path)
```

2 - Policy experiments setup and export

November 19, 2018

In [ ]:
```
import numpy as np
import pandas as pd
import os
import feather
import datetime
import seaborn as sns

from ema_workbench import (Model,
                           RealParameter,
                           IntegerParameter,
                           Constant,
                           TimeSeriesOutcome,
                           perform_experiments,
                           ema_logging,
                           save_results,
                           perform_experiments,
                           ema_logging,
                           Policy,
                           load_results)

from ema_workbench.connectors.vensim import VensimModel

import ema_workbench.analysis.pairs_plotting as pairs
import ema_workbench.analysis.plotting as emaplt
from ema_workbench.analysis.plotting import lines
from ema_workbench.analysis.plotting_util import KDE

import matplotlib.pyplot as plt

# turn on logging
ema_logging.log_to_stderr(ema_logging.INFO)
```

In [ ]:
```
# Function to easily save all outcomes of interest
def export_outcomes(outcomes, label):
    """takes EMA outcomes and exports all time series for each outcome of interest as
    import into R. Arguments: export_outcomes(name of EMA outcomes dict, desired save
    defaults to './Data/'.
```

```
    """
    location = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/" + label + "_KPI_'
    today = datetime.date.today()
    datestr = (str(today))

    keylist = list(outcomes.keys())

    for k in keylist:
        df_temp = pd.DataFrame(outcomes[k])
        df_temp = df_temp.copy()
        path = location + datestr + k.replace(' ','') + '.feather'
        feather.write_dataframe(df_temp,path)

    return("Done.");

# Function for creating line plots with density maps for observed interests
def plot_interests(interests, label, experiments_to_show, save):
    prefix = str(label)
    for kpi in interests:
        fig, axes = lines(results, outcomes_to_show=kpi,density=KDE,experiments_to_shov
        if save == 'y':
            plt.savefig('{}/fig_{}_highres.png'.format("Z:\stack\Documenten\TU\EPA\MSc_
        else:
            print(str(kpi)+'figure not saved')
    plt.show()

# Function for creating line plots grouped by policy for defined polies
def plot_interests_def(interests, label, experiments_to_show, save):
    prefix = str(label)
    for kpi in interests:
        fig, axes = lines(results, group_by='policy', outcomes_to_show=kpi, density=KDI
                                          legend=True, experiments_to_show=np.random.ra
        fig.set_size_inches(8,5.2)
        if save == 'y':
            plt.savefig('{}/fig_{}_highres.png'.format("Z:\stack\Documenten\TU\EPA\MSc_
        else:
            print(str(kpi)+'figure not saved')
    plt.show()
```

1 Mixed policies

First, the model must be loaded and parameters should be set.

In [ ]:
```
# Load basic model for scenario discovery
wd = r'./Model'
model = VensimModel("Mixed", wd=wd, model_file=r'Modelv9Policies.vpm')
```

```python
In [ ]: # Define uncertainty ranges
        uncertainties = [
                        RealParameter("Alternative_technology_introduction_year",2000,2030),
                        RealParameter("Alternative_vehicle_technology_max_attractiveness",0,8)
                        RealParameter("Alternative_vehicle_development_speed",0.05,0.35),
                        RealParameter("BEV_development_speed",0.1,0.2),
                        RealParameter("Risk_premium_ratio_NWC",0,1),
                        RealParameter("ICE_average_fuel_price",0.80,1.60),
                        RealParameter("ROI_aim_ratio_NWC",0,2),
                        RealParameter("NWC_public_incentive_investment_boost",0,1),
                        RealParameter("Initial_market_share_NWC", 0,1),
                        RealParameter("learning_curve_period_EVCS_cost",2,4),
                        RealParameter("learning_curve_period_charging_speed",2,4),
                        RealParameter("Progress_ratio_EVCS_cost",0.5,0.7),
                        RealParameter("Progress_ratio_EVCS_charging_speed",0.3,0.5)
                        ]

        # Formulate outcomes of interest
        outcomes =  [
                        TimeSeriesOutcome("EVCS_price_per_kWh"), #
                        TimeSeriesOutcome("BEV_sales_share"),
                        TimeSeriesOutcome("Market_share_semi_public"),
                        TimeSeriesOutcome("ROI_Commercial"),
                        TimeSeriesOutcome("CAPEX_gap"),
                        TimeSeriesOutcome("EVCS_per_BEV")
                    ]

        # Define policy levers
        levers = [
                        RealParameter("Market_entry_period",5,20),
                        IntegerParameter("No_entry_switch",0,1),
                        RealParameter("Market_share_cap",0,1),
                        IntegerParameter("Shareholder_activation_switch",0,1)
        ]

        # Override some of the constants in the model for quick access
        constants = [
                        Constant("Initial_active_EVCS", 200),
                        Constant("Initial_EVCS_in_preparation",200),
                        Constant("time_to_adjust_price",3),
                        Constant("Delay_attractiveness_effect",5),
                        Constant("ROI_aim",0.2),
                        Constant("Initial_charging_fee",3)
                    ]
```

Assign model settings and perform experiments.

```python
In [ ]: # Assign model settings
        model.uncertainties = uncertainties
```

```
    model.outcomes = outcomes
    model.constants = constants
    model.levers = levers

    # Perform experiments
    nr_experiments = 1000
    nr_policies = 10
    results = perform_experiments(model, scenarios = nr_experiments, policies = nr_policie:

    experiments, outcomes = results
```

```
In [ ]: save_results(results, 'Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/Policies_10(
```

1.0.1 Plot interests for explorations phase

The model data has been saved before and loaded separately here to allow easy reuse of the data. Also, the data export will be done after exploration, for simulation errors can also be spotted in the exploration phase.

```
In [ ]: # load data
        data = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/Policies_10000scenarios.ta:
        results = load_results(data)

        nr_experiments = 10000
        experiments, outcomes = results
```

```
In [ ]: # Created two different sets for outcome plotting in order to prevent memory errors
        interests1 = ["EVCS_price_per_kWh","BEV_sales_share","Market_share_semi_public"]
        interests2 = ["ROI_Commercial","CAPEX_gap","EVCS_per_BEV"]
```

```
In [ ]: plot_interests(interests1, 'Policies', 10000, 'n')
```

```
In [ ]: plot_interests(interests2, 'Policies', 10000, 'n')
```

1.0.2 Data export

Exporting data using feather. This package enables easy data transfer between Python and R.

```
In [ ]: # Export all outcomes
        export_outcomes(outcomes, "Policies")
```

```
In [ ]: # Exporting experiments data
        filelabel = "Policies"
        df_expt = pd.DataFrame(experiments) #create dataframe from experiments (array of tuple.
        for i, row in df_expt.iterrows():
            df_expt.set_value(i,'policy',1) #otherwise float error at no policies
        df_expt2 = df_expt.iloc[:,0:-1].astype("float")
        df_expt2 = df_expt2.copy() #self-copy to circumvent errors
        path = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/" + filelabel + "_" + str(
        feather.write_dataframe(df_expt2,path)
```

2 Defined policies

First, the model must be loaded and parameters should be set.

```
In [ ]: # Load basic model for scenario discovery
        wd = r'./Model'
        policies_model = VensimModel("BaseCase", wd=wd, model_file=r'Modelv9NoPolicy.vpm')
```

```
In [ ]: # Define experiment parameters

        # Define uncertainty ranges
        uncertainties = [
                        RealParameter("Alternative_technology_introduction_year",2000,2030), #
                        RealParameter("Alternative_vehicle_technology_max_attractiveness",0,8)
                        RealParameter("Alternative_vehicle_development_speed",0.05,0.35),
                        RealParameter("BEV_development_speed",0.1,0.2),
                        RealParameter("Risk_premium_ratio_NWC",0,1),
                        RealParameter("ICE_average_fuel_price",0.80,1.60),
                        RealParameter("ROI_aim_ratio_NWC",0,2),
                        RealParameter("NWC_public_incentive_investment_boost",0,1),
                        RealParameter("Initial_market_share_NWC", 0,1),
                        RealParameter("learning_curve_period_EVCS_cost",2,4),
                        RealParameter("learning_curve_period_charging_speed",2,4),
                        RealParameter("Progress_ratio_EVCS_cost",0.5,0.7),
                        RealParameter("Progress_ratio_EVCS_charging_speed",0.3,0.5)
                        ]

        # Formulate outcomes of interest
        outcomes =  [
                        TimeSeriesOutcome("EVCS_price_per_kWh"), #
                        TimeSeriesOutcome("BEV_sales_share"),
                        TimeSeriesOutcome("Market_share_semi_public"),
                        TimeSeriesOutcome("ROI_Commercial"),
                        TimeSeriesOutcome("CAPEX_gap"),
                        TimeSeriesOutcome("EVCS_per_BEV"),
                    ]

        # Define policies
        policies = [    Policy('NoPolicy', model_file=r'Modelv9NoPolicy.vpm'),
                        Policy('NoEntry', model_file=r'Modelv9NoEntry.vpm'),
                        Policy('MarketEntry', model_file=r'Modelv9MarketEntry5y.vpm'),
                        Policy('MarketShareCap', model_file=r'Modelv9MarketShareCap.vpm'),
                        Policy('ShareholderActivation', model_file=r'Modelv9ShareholderActivat
                        ]

        # Override some of the constants in the model for quick access
        constants = [
                        Constant("Initial_active_EVCS", 200), # Initial amount of active EVCS
```

```
                    Constant("Initial_EVCS_in_preparation",200), # Initial amount of EVCS 
                    Constant("time_to_adjust_price",3), # Time delay of market price avera
                    Constant("Delay_attractiveness_effect",5),
                    Constant("ROI_aim",0.2),
                    Constant("Initial_charging_fee",3)
                ]
```

Assign model settings and perform experiments

```
In [ ]: # Assign model settings
        policies_model.uncertainties = uncertainties
        policies_model.outcomes = outcomes
        policies_model.constants = constants

        # Perform experiments
        nr_experiments = 1000
        results = perform_experiments(policies_model, scenarios = nr_experiments, policies = po

        experiments, outcomes = results
```

```
In [ ]: save_results(results, 'Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/5_policies_
```

2.0.1 Plot interests for explorations phase

The model data has been saved before and loaded separately here to allow easy reuse of the data. Also, the data export will be done after exploration, for simulation errors can also be spotted in the exploration phase.

```
In [ ]: # load data
        data = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/5_policies_1000_scenarios.t
        results = load_results(data)

        experiments, outcomes = results
        nr_experiments = 5000
```

```
In [ ]: plot_interests_def(interests1, "Defined_policies", 600, 'y')
```

```
In [ ]: plot_interests_def(interests2, "Defined_policies", 500, 'y')
```

2.0.2 Data export

Exporting data using feather. This package enables easy data transfer between Python and R.

```
In [ ]: # Export all outcomes
        export_outcomes(outcomes, "Defined_Policies")
```

```
In [ ]: filelabel = 'Defined_Policies'
        df_expt = pd.DataFrame(experiments) #create dataframe from experiments (array of tuple

        # Rename policies into floats to allow data transfer
```

```python
for i, row in df_expt.iterrows():
    if df_expt['policy'][i] == 'NoPolicy':
        df_expt.set_value(i,'policy',0)
    if df_expt['policy'][i] == 'NoEntry':
        df_expt.set_value(i,'policy',1)
    if df_expt['policy'][i] == 'MarketEntry':
        df_expt.set_value(i,'policy',2)
    if df_expt['policy'][i] == 'MarketShareCap':
        df_expt.set_value(i,'policy',3)
    if df_expt['policy'][i] == 'ShareholderActivation':
        df_expt.set_value(i,'policy',4)

df_expt2 = df_expt.iloc[:,0:-1].astype("float")
df_expt2 = df_expt2.copy() #self-copy to circumvent errors
path = "Z:\stack\Documenten\TU\EPA\MSc_Thesis\Analysis\Data/" + filelabel + "_" + str(
feather.write_dataframe(df_expt2,path) #feather it!
```

3 - SOBOL No Policy

November 19, 2018

```
In [ ]: import numpy as np
        import pandas as pd
        import os
        import feather
        import datetime
        import seaborn as sns

        from ema_workbench import (Model,
                                   RealParameter,
                                   IntegerParameter,
                                   Constant,
                                   TimeSeriesOutcome,
                                   perform_experiments,
                                   ema_logging,
                                   save_results,
                                   perform_experiments,
                                   ema_logging,
                                   MultiprocessingEvaluator,
                                   load_results)

        from ema_workbench.connectors.vensim import VensimModel

        import ema_workbench.analysis.pairs_plotting as pairs
        import ema_workbench.analysis.plotting as emaplt
        from ema_workbench.analysis.plotting import lines
        from ema_workbench.analysis.plotting_util import KDE

        import matplotlib.pyplot as plt

        from SALib.analyze import sobol
        from ema_workbench.em_framework.salib_samplers import get_SALib_problem
        from ema_workbench.em_framework.salib_samplers import SobolSampler

        from __future__ import (unicode_literals, print_function, absolute_import,
                                division)

        import math
```

```
import numpy as np
import pandas as pd
from scipy.optimize import brentq

from SALib.analyze import sobol


from ema_workbench import (Model, RealParameter, ScalarOutcome, Constant,
                           ema_logging, MultiprocessingEvaluator, Policy)
from ema_workbench.em_framework.evaluators import SOBOL
from ema_workbench.em_framework import get_SALib_problem

# turn on logging
ema_logging.log_to_stderr(ema_logging.INFO)
```

1 Load specific No policy SOBOL model

The same model but with a slightly larger timestep has been used to increase simulation speed. Sobol requires high amounts of experiments, therefore smaller timesteps were experienced to be problematic.

```
In [ ]: # Load basic model for scenario discovery
        wd = r'./Model'
        model = VensimModel("NoPolicy", wd=wd, model_file=r'Modelv9NoPolicy_SOBOL.vpm')
```

```
In [ ]: # Define experiment parameters

        # Define uncertainty ranges
        uncertainties = [
                        RealParameter("Alternative_technology_introduction_year",2000,2030), #
                        RealParameter("Alternative_vehicle_technology_max_attractiveness",0,8)
                        RealParameter("Alternative_vehicle_development_speed",0.05,0.35),
                        RealParameter("BEV_development_speed",0.1,0.2),
                        RealParameter("Risk_premium_ratio_NWC",0,1),
                        RealParameter("ICE_average_fuel_price",0.80,1.60),
                        RealParameter("ROI_aim_ratio_NWC",0,2),
                        RealParameter("NWC_public_incentive_investment_boost",0,1),
                        RealParameter("Initial_market_share_NWC", 0,1),
                        RealParameter("learning_curve_period_EVCS_cost",2,4),
                        RealParameter("learning_curve_period_charging_speed",2,4),
                        RealParameter("Progress_ratio_EVCS_cost",0.5,0.7),
                        RealParameter("Progress_ratio_EVCS_charging_speed",0.3,0.5)
                        ]

        # Formulate outcomes of interest
        outcomes =  [
                        TimeSeriesOutcome("EVCS_price_per_kWh"), #
```

```
                         TimeSeriesOutcome("BEV_sales_share"),
                         TimeSeriesOutcome("Market_share_semi_public"),
                         TimeSeriesOutcome("ROI_Commercial"),
                         TimeSeriesOutcome("CAPEX_gap"),
                         TimeSeriesOutcome("EVCS_per_BEV")
                     ]

        # Override some of the constants in the model for quick access
        constants = [
                         Constant("Initial_active_EVCS", 200), # Initial amount of active EVCS
                         Constant("Initial_EVCS_in_preparation",200), # Initial amount of EVCS
                         Constant("time_to_adjust_price",3), # Time delay of market price avera
                         Constant("Delay_attractiveness_effect",5),
                         Constant("ROI_aim",0.2),
                         Constant("Initial_charging_fee",3)
                # to do: add OPEX and CAPEX constants
                     ]
```

```
In [ ]: # Assign model settings
        model.uncertainties = uncertainties
        model.outcomes = outcomes
        model.constants = constants
```

```
In [ ]: with MultiprocessingEvaluator(model, n_processes=4) as evaluator:
            sa_results = evaluator.perform_experiments(scenarios=1000,uncertainty_sampling=SOB

        experiments, outcomes = sa_results
```

```
In [ ]: save_results(sa_results, 'Data/SOBOL_NoPolicy_1000scenarios280000exp.tar.gz')
```

2 Outcome visualisation

```
In [ ]: # load data
        data = "Data/SOBOL_NoPolicy_1000scenarios28000exp.tar.gz"
        sa_results = load_results(data)

        experiments, outcomes = sa_results
```

```
In [ ]: # Function to create bar plots for Sobol indices

        def SOBOLplot(targetyear, targetoutcome, resultsdata, save, policyname):
            # Change outcomes format from timeseries to single numpy array
            experiments, outcomes = resultsdata

            newoutcomes = []
            for j in range(len(outcomes[targetoutcome])):
                for i in range(len(outcomes['TIME'][0])):
                    if outcomes['TIME'][0][i] == targetyear:
```

```
                newoutcomes.append(outcomes[targetoutcome][j][i])
        outcome = np.array(newoutcomes)

        problem = get_SALib_problem(model.uncertainties)
        Si = sobol.analyze(problem, outcome,
                           calc_second_order=True, print_to_console=False)

        # Create plot:
        scores_filtered = {k:Si[k] for k in ['ST','ST_conf','S1','S1_conf']}
        Si_df = pd.DataFrame(scores_filtered, index=problem['names'])

        sns.set_style('white')
        fig, ax = plt.subplots(1)

        indices = Si_df[['S1','ST']]
        err = Si_df[['S1_conf','ST_conf']]

        indices.plot.bar(yerr=err.values.T,ax=ax)
        fig.set_size_inches(8,6)
        fig.subplots_adjust(bottom=0.3)

        if save == 'y':
            plt.savefig('{}/{}_highres.png'.format("Z:\stack\Documenten\TU\EPA\MSc_Thesis\
            plt.show()
        else:
            plt.show()
```

```
In [ ]: policy = 'No_Policy'
        save = 'y'
```

2.0.1 BEV sales share

```
In [ ]: SOBOLplot(2020, 'BEV_sales_share', sa_results, save, policy)
        SOBOLplot(2030, 'BEV_sales_share', sa_results, save, policy)
```

2.0.2 CAPEX gap

```
In [ ]: SOBOLplot(2013, 'CAPEX_gap', sa_results, save, policy)
        SOBOLplot(2030, 'CAPEX_gap', sa_results, save, policy)
```

2.0.3 EVCS price per kWh

```
In [ ]: SOBOLplot(2013, 'EVCS_price_per_kWh', sa_results, save, policy)
        SOBOLplot(2025, 'EVCS_price_per_kWh', sa_results, save, policy)
```

2.0.4 Market share NWC

```
In [ ]: SOBOLplot(2013, 'Market_share_semi_public', sa_results, save, policy)
        SOBOLplot(2017, 'Market_share_semi_public', sa_results, save, policy)
```

```
SOBOLplot(2030, 'Market_share_semi_public', sa_results, save, policy)
```

2.0.5 ROI Commercial

```
In [ ]: SOBOLplot(2012.25, 'ROI_Commercial', sa_results, save, policy)
        SOBOLplot(2014, 'ROI_Commercial', sa_results, save, policy)
        SOBOLplot(2028, 'ROI_Commercial', sa_results, save, policy)
```

3 Combined short- and long-term dataframes

```
In [ ]: def SOBOLindices(targetyear, targetoutcome, save, policyname):
            experiments, outcomes = sa_results

            newoutcomes = []
            for j in range(len(outcomes[targetoutcome])):
                for i in range(len(outcomes['TIME'][0])):
                    if outcomes['TIME'][0][i] == targetyear:
                        newoutcomes.append(outcomes[targetoutcome][j][i])
            outcome = np.array(newoutcomes)

            problem = get_SALib_problem(model.uncertainties)
            Si = sobol.analyze(problem, outcome,
                               calc_second_order=True, print_to_console=False)

            # Create plot:
            scores_filtered = {k:Si[k] for k in ['ST','S1']}
            Si_df = pd.DataFrame(scores_filtered, index=problem['names'])
            Si_df[targetoutcome, 'ST'] = Si_df['ST']
            Si_df[targetoutcome, 'S1'] = Si_df['S1']
            Si_df = Si_df.drop(['S1', 'ST'], axis=1)
            Si_df.columns = pd.MultiIndex.from_tuples(Si_df.columns)
            return Si_df

        def SOBOLcombined(targetyear, interests, save, policyname):
            Si_dfc = pd.DataFrame()

            for kpi in interests:
                df_aux = SOBOLindices(targetyear, kpi, save, policyname)
                Si_dfc = pd.concat([Si_dfc, df_aux], axis=1)

            return Si_dfc

In [ ]: save = 'n'
        policyname = 'NoPolicy'
        interests = ["EVCS_price_per_kWh","BEV_sales_share","Market_share_semi_public","ROI_Co

        Si_df2013 = SOBOLcombined(2013, interests, save, policyname)
```

```
Si_df2015 = SOBOLcombined(2015, interests, save, policyname)
Si_df2030 = SOBOLcombined(2030, interests, save, policyname)
```

In [ ]:
```
Shortterm = pd.ExcelWriter('SOBOLshortNoPolicy.xlsx')
Si_df2013.to_excel(Shortterm,'2013')
Si_df2015.to_excel(Shortterm,'2015')
Longterm = pd.ExcelWriter('SOBOLlongNoPolicy.xlsx')
Si_df2030.to_excel(Longterm, '2030')
Shortterm.save()
Longterm.save()
```

4 Second order indices

In [ ]:
```
def SOBOLsecondorder(targetyear, targetoutcome, save, policyname):
    experiments, outcomes = sa_results

    newoutcomes = []
    for j in range(len(outcomes[targetoutcome])):
        for i in range(len(outcomes['TIME'][0])):
            if outcomes['TIME'][0][i] == targetyear:
                newoutcomes.append(outcomes[targetoutcome][j][i])
    outcome = np.array(newoutcomes)

    problem = get_SALib_problem(model.uncertainties)
    Si = sobol.analyze(problem, outcome,
                calc_second_order=True, print_to_console=False)

    colnames = []
    for word in problem['names']:
        word1 = word.replace("_", " ")
        colnames.append(word1)
    colnames

    Allvars = {}
    for i in range(len(colnames)):
        Varlist = []
        for j in range(len(colnames)):
            Varlist.append(round(Si['S2'][i,j],4))
        Allvars[str(i)] = Varlist

    Si_df2 = pd.DataFrame(Allvars, index=colnames)
    Si_df2.columns = colnames

    fig, ax = plt.subplots(figsize=(12,5))
    ax.set_title('S2 ' + targetoutcome + " " + str(targetyear) + " at " + policyname)
    sns.heatmap(Si_df2, annot=True, cmap="Blues", linewidths=1, linecolor='white', ax=a
    if save == 'y':
```

```python
                plt.savefig("S2_" + targetoutcome + "_" + str(targetyear) + "_" + policyname +
                plt.show()
            else:
                print("figure not saved")
                plt.show()
```

In [ ]:
```python
policyname = "NoPolicy"
secondorder_interests = ["BEV_sales_share","Market_share_semi_public","ROI_Commercial"]
save = 'y'
targetyears = [2013, 2020, 2030]

for kpi in secondorder_interests:
    for year in targetyears:
        SOBOLsecondorder(year, kpi, save, policyname)
```

4 - SOBOL Mixed Policies

November 19, 2018

In [ ]:
```
import numpy as np
import pandas as pd
import os
import feather
import datetime
import seaborn as sns

from ema_workbench import (Model,
                           RealParameter,
                           IntegerParameter,
                           Constant,
                           TimeSeriesOutcome,
                           perform_experiments,
                           ema_logging,
                           save_results,
                           perform_experiments,
                           ema_logging,
                           MultiprocessingEvaluator,
                           load_results)

from ema_workbench.connectors.vensim import VensimModel

import ema_workbench.analysis.pairs_plotting as pairs
import ema_workbench.analysis.plotting as emaplt
from ema_workbench.analysis.plotting import lines
from ema_workbench.analysis.plotting_util import KDE

import matplotlib.pyplot as plt

from SALib.analyze import sobol
from ema_workbench.em_framework.salib_samplers import get_SALib_problem
from ema_workbench.em_framework.salib_samplers import SobolSampler

from __future__ import (unicode_literals, print_function, absolute_import,
                        division)

import math
```

```python
import numpy as np
import pandas as pd
from scipy.optimize import brentq

from SALib.analyze import sobol


from ema_workbench import (Model, RealParameter, ScalarOutcome, Constant,
                           ema_logging, MultiprocessingEvaluator, Policy)
from ema_workbench.em_framework.evaluators import SOBOL
from ema_workbench.em_framework import get_SALib_problem

# turn on logging
ema_logging.log_to_stderr(ema_logging.INFO)
```

1 Load specific Mixed policies SOBOL model

The same model but with a slightly larger timestep has been used to increase simulation speed. Sobol requires high amounts of experiments, therefore smaller timesteps were experienced to be problematic.

```python
In [ ]: # Load basic model for scenario discovery
        wd = r'./Model'
        model = VensimModel("Mixed", wd=wd, model_file=r'Modelv9Levers_SOBOL.vpm')
```

```python
In [ ]: # Define experiment parameters

        # Define uncertainty ranges. LEVERS added as well to enable SOBOl analysis.
        uncertainties = [
                        RealParameter("Alternative_technology_introduction_year",2000,2030), #
                        RealParameter("Alternative_vehicle_technology_max_attractiveness",0,8)
                        RealParameter("Alternative_vehicle_development_speed",0.05,0.35),
                        RealParameter("BEV_development_speed",0.1,0.2),
                        RealParameter("Risk_premium_ratio_NWC",0,1),
                        RealParameter("ICE_average_fuel_price",0.80,1.60),
                        RealParameter("ROI_aim_ratio_NWC",0,2),
                        RealParameter("NWC_public_incentive_investment_boost",0,1),
                        RealParameter("Initial_market_share_NWC", 0,1),
                        RealParameter("learning_curve_period_EVCS_cost",2,4),
                        RealParameter("learning_curve_period_charging_speed",2,4),
                        RealParameter("Progress_ratio_EVCS_cost",0.5,0.7),
                        RealParameter("Progress_ratio_EVCS_charging_speed",0.3,0.5),
                        RealParameter("Market_entry_period",5,20),
                        IntegerParameter("No_entry_switch",0,1),
                        RealParameter("Market_share_cap",0,1),
                        IntegerParameter("Shareholder_activation_switch",0,1)
                        ]
```

```
# Formulate outcomes of interest
outcomes =  [
                TimeSeriesOutcome("EVCS_price_per_kWh"), #
                TimeSeriesOutcome("BEV_sales_share"),
                TimeSeriesOutcome("Market_share_semi_public"),
                TimeSeriesOutcome("ROI_Commercial"),
                TimeSeriesOutcome("CAPEX_gap")
            ]

# Override some of the constants in the model for quick access
constants = [
                Constant("Initial_active_EVCS", 200), # Initial amount of active EVCS
                Constant("Initial_EVCS_in_preparation",200), # Initial amount of EVCS
                Constant("time_to_adjust_price",3), # Time delay of market price avera
                Constant("Delay_attractiveness_effect",5),
                Constant("ROI_aim",0.2),
                Constant("Initial_charging_fee",3)
    # to do: add OPEX and CAPEX constants
            ]
```

```
In [ ]: interests = ["EVCS_price_per_kWh","BEV_sales_share","Market_share_semi_public","ROI_Co
```

```
In [ ]: # Assign model settings
        model.uncertainties = uncertainties
        model.outcomes = outcomes
        model.constants = constants
```

```
In [ ]: with MultiprocessingEvaluator(model, n_processes=4) as evaluator:
            sa_results = evaluator.perform_experiments(scenarios=1000,uncertainty_sampling=SOB

        experiments, outcomes = sa_results
```

```
In [ ]: save_results(sa_results, 'Data/SOBOL_Mixed_1000scenarios36000exp.tar.gz')
```

2 Outcomes visualisation

```
In [ ]: # load data
        data = "Data/SOBOL_Mixed_1000scenarios36000exp.tar.gz"
        sa_results = load_results(data)

        experiments, outcomes = sa_results
```

```
In [ ]: def SOBOLplot(targetyear, targetoutcome, resultsdata, save, policyname):
            # Change outcomes format from timeseries to single numpy array
            experiments, outcomes = resultsdata

            newoutcomes = []
            for j in range(len(outcomes[targetoutcome])):
```

```
        for i in range(len(outcomes['TIME'][0])):
            if outcomes['TIME'][0][i] == targetyear:
                newoutcomes.append(outcomes[targetoutcome][j][i])
    outcome = np.array(newoutcomes)

    problem = get_SALib_problem(model.uncertainties)
    Si = sobol.analyze(problem, outcome,
                       calc_second_order=True, print_to_console=False)

    # Create plot:
    scores_filtered = {k:Si[k] for k in ['ST','ST_conf','S1','S1_conf']}
    Si_df = pd.DataFrame(scores_filtered, index=problem['names'])

    sns.set_style('white')
    fig, ax = plt.subplots(1)

    indices = Si_df[['S1','ST']]
    err = Si_df[['S1_conf','ST_conf']]

    indices.plot.bar(yerr=err.values.T,ax=ax)
    fig.set_size_inches(8,6)
    fig.subplots_adjust(bottom=0.3)

    if save == 'y':
        plt.savefig('{}/{}_highres.png'.format("Z:\stack\Documenten\TU\EPA\MSc_Thesis\
        plt.show()
    else:
        plt.show()
```

```
In [ ]: policy = 'Mixed'
        save = 'y'
```

2.0.1 BEV sales share

```
In [ ]: SOBOLplot(2020, 'BEV_sales_share', sa_results, save, policy)
        SOBOLplot(2030, 'BEV_sales_share', sa_results, save, policy)
```

2.0.2 CAPEX gap

```
In [ ]: SOBOLplot(2018.5, 'CAPEX_gap', sa_results, save, policy)
        SOBOLplot(2030, 'CAPEX_gap', sa_results, save, policy)
```

2.0.3 EVCS price per kWh

```
In [ ]: SOBOLplot(2013, 'EVCS_price_per_kWh', sa_results, save, policy)
        SOBOLplot(2025, 'EVCS_price_per_kWh', sa_results, save, policy)
        SOBOLplot(2030, 'EVCS_price_per_kWh', sa_results, save, policy)
```

2.0.4 Market share NWC

Some policies directly influence this KPI and therefore new outcomes are predictable. Therefore, the lineplot will be used as a reference rather than a performance indicator.

2.0.5 ROI Commercial

```
In [ ]: SOBOLplot(2012.25, 'ROI_Commercial', sa_results, save, policy)
        SOBOLplot(2014, 'ROI_Commercial', sa_results, save, policy)
        SOBOLplot(2030, 'ROI_Commercial', sa_results, save, policy)
```

3 Market share NWC

```
In [ ]: SOBOLplot(2013.75, 'Market_share_semi_public', sa_results, save, policy)
        SOBOLplot(2030, 'Market_share_semi_public', sa_results, save, policy)
```

4 Combined short- and long-term dataframes

```
In [ ]: def SOBOLindices(targetyear, targetoutcome, save, policyname):
            experiments, outcomes = sa_results

            newoutcomes = []
            for j in range(len(outcomes[targetoutcome])):
                for i in range(len(outcomes['TIME'][0])):
                    if outcomes['TIME'][0][i] == targetyear:
                        newoutcomes.append(outcomes[targetoutcome][j][i])
            outcome = np.array(newoutcomes)

            problem = get_SALib_problem(model.uncertainties)
            Si = sobol.analyze(problem, outcome,
                                calc_second_order=True, print_to_console=False)

            # Create plot:
            scores_filtered = {k:Si[k] for k in ['ST','S1']}
            Si_df = pd.DataFrame(scores_filtered, index=problem['names'])
            Si_df[targetoutcome, 'ST'] = Si_df['ST']
            Si_df[targetoutcome, 'S1'] = Si_df['S1']
            Si_df = Si_df.drop(['S1', 'ST'], axis=1)
            Si_df.columns = pd.MultiIndex.from_tuples(Si_df.columns)
            return Si_df

        def SOBOLcombined(targetyear, interests, save, policyname):
            Si_dfc = pd.DataFrame()

            for kpi in interests:
                df_aux = SOBOLindices(targetyear, kpi, save, policyname)
                Si_dfc = pd.concat([Si_dfc, df_aux], axis=1)
```

```
        return Si_dfc
```

In [ ]:
```
save = 'n'
policyname = 'Policies'
interests = ["EVCS_price_per_kWh","BEV_sales_share","Market_share_semi_public","ROI_Co

Si_df2013 = SOBOLcombined(2013, interests, save, policyname)
Si_df2015 = SOBOLcombined(2015, interests, save, policyname)
Si_df2030 = SOBOLcombined(2030, interests, save, policyname)
```

In [ ]:
```
Shortterm = pd.ExcelWriter('SOBOLshortPolicies.xlsx')
Si_df2013.to_excel(Shortterm,'2013')
Si_df2015.to_excel(Shortterm,'2015')
Longterm = pd.ExcelWriter('SOBOLlongPolicies.xlsx')
Si_df2030.to_excel(Longterm, '2030')
Shortterm.save()
Longterm.save()
```

5 Second order indices

In [ ]:
```
def SOBOLsecondorder(targetyear, targetoutcome, save, policyname):
    experiments, outcomes = sa_results

    newoutcomes = []
    for j in range(len(outcomes[targetoutcome])):
        for i in range(len(outcomes['TIME'][0])):
            if outcomes['TIME'][0][i] == targetyear:
                newoutcomes.append(outcomes[targetoutcome][j][i])
    outcome = np.array(newoutcomes)

    problem = get_SALib_problem(model.uncertainties)
    Si = sobol.analyze(problem, outcome,
                    calc_second_order=True, print_to_console=False)

    colnames = []
    for word in problem['names']:
        word1 = word.replace("_", " ")
        colnames.append(word1)
    colnames

    Allvars = {}
    for i in range(len(colnames)):
        Varlist = []
        for j in range(len(colnames)):
            Varlist.append(round(Si['S2'][i,j],4))
        Allvars[str(i)] = Varlist
```

```
        Si_df2 = pd.DataFrame(Allvars, index=colnames)
        Si_df2.columns = colnames

        fig, ax = plt.subplots(figsize=(17,8))
        ax.set_title('S2 ' + targetoutcome + " " + str(targetyear) + " at " + policyname)
        sns.heatmap(Si_df2, annot=True, cmap="Blues", linewidths=1, linecolor='white', ax=a
        if save == 'y':
            plt.savefig("S2_" + targetoutcome + "_" + str(targetyear) + "_" + policyname +
            plt.show()
        else:
            print("figure not saved")
            plt.show()
```

```
In [ ]: policyname = "Policies"
        secondorder_interests = ["CAPEX_gap","EVCS_price_per_kWh","ROI_Commercial", "Market_sha
        save = 'y'
        targetyears = [2014, 2030]

        for kpi in secondorder_interests:
            for year in targetyears:
                SOBOLsecondorder(year, kpi, save, policyname)
```

F

R Scripts

The R scripts for the behaviour based scenario discovery are added here.

```
#adjust working directory
getwd()
setwd("/Users/freekakkermans/stack/Documenten/TU/EPA/MSc_Thesis/Analysis")
wd <- getwd()

#load functions -> Premade functions by Patrick Steinmann have been used. Publicy available through
github.com/steipatr
source("SteiPatr_BBSD_R_Functions.R")

#load libraries
library("feather")
library("Cairo")
library("caret")

policy <- "NoPolicy"

#load data
data_date <- "2018-10-15"
outcomeslist <-
list("ROI_Commercial","Market_share_semi_public","EVCS_price_per_kWh","BEV_sales_share","CAPEX_gap")


for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,data_date,".feather", sep="")

  df_outcomes <- read_feather(path_outcomes)

  # Estimating Cluster Count
  # Selecting method for clustering: choose from
("ACF","CID","CORT","DWT","LLR","LPC","PDC","PER","PIC","DTW","SBD","GAK","TAD","LCM")
  # Steinmann, R. (2018): CID, CORT and DWT most accurate
  cl_methods <- c("CID", "CORT", "DWT")

  df_sils <- compare.silhouettes(df_outcomes,cl_methods,kmin=2,kmax=6,kstep=1,logging=TRUE)

  #plot silhouette trajectories
  df_sils_long <- melt(df_sils,id.vars = c("k"),variable.name="method")
  sil_plt <- ggplot(df_sils_long, aes(x = k, y = value,color=method, group = method)) + geom_point() +
geom_line() +
    xlab("k") + ylab("silhouette width")
  plot(sil_plt)

  #export plot
  saveloc <- paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_","Silhouettes.png",sep="")
  ggsave(plot = sil_plt, saveloc, h = 5, w = 8, type = "cairo-png")
}


# Clustering:
# get k values from silhouette plot
klist <- list("ROI_Commercial" = 4, "Market_share_semi_public" = 4, "EVCS_price_per_kWh" = 3,
"BEV_sales_share" = 3, "CAPEX_gap" = 4, "BEV_share" = 3)


## Clustering with CID:

mthd = "CID"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  #df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])
  # Load already clustered outcomes:
  data_clustering_date <- "2018-10-16"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")
  df_cl <- read_feather(path_clusters)


  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CID")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
```

```
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with CORT:

mthd = "CORT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CORT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with DWT:

mthd = "DWT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"DWT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 2.5, w = 4, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}





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# Policy option interactions

policy <- "Policies"
outcomeslist <- list("CAPEX_gap", "BEV_sales_share","ROI_Commercial","EVCS_price_per_kWh")
data_date <- "2018-10-24"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,data_date,".feather", sep="")
```

```r
  df_outcomes <- read_feather(path_outcomes)

  # Estimating Cluster Count
  # Selecting method for clustering: choose from
("ACF","CID","CORT","DWT","LLR","LPC","PDC","PER","PIC","DTW","SBD","GAK","TAD","LCM")
  # Steinmann, R. (2018): CID, CORT and DWT most accurate
  cl_methods <- c("CID", "CORT", "DWT")

  df_sils <- compare.silhouettes(df_outcomes,cl_methods,kmin=2,kmax=8,kstep=1,logging=TRUE)

  #plot silhouette trajectories
  df_sils_long <- melt(df_sils,id.vars = c("k"),variable.name="method")
  sil_plt <- ggplot(df_sils_long, aes(x = k, y = value,color=method, group = method)) + geom_point() +
geom_line() +
    xlab("k") + ylab("silhouette width")
  plot(sil_plt)

  #export plot
  saveloc <- paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_","Silhouettes.png",sep="")
  ggsave(plot = sil_plt, saveloc, h = 5, w = 8, type = "cairo-png")
}

# Clustering:
# get k values from silhouette plot
klist <- list("ROI_Commercial" = 2, "EVCS_price_per_kWh" = 3, "BEV_sales_share" = 2, "CAPEX_gap" = 3)

## Clustering with CID:

mthd = "CID"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  # df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])
  # Load already clustered outcomes:
  data_clustering_date <- "2018-10-24"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")
  df_cl <- read_feather(path_clusters)


  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CID")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with CORT:

mthd = "CORT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CORT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
```

```
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with DWT:

mthd = "DWT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"DWT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}



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# Defined policies

policy <- "Defined_Policies"
outcomeslist <- list("ROI_Commercial","EVCS_price_per_kWh","CAPEX_gap", "BEV_sales_share") #

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,data_date,".feather", sep="")

  df_outcomes <- read_feather(path_outcomes)

  # Estimating Cluster Count
  # Selecting method for clustering: choose from
("ACF","CID","CORT","DWT","LLR","LPC","PDC","PER","PIC","DTW","SBD","GAK","TAD","LCM")
  # Steinmann, R. (2018): CID, CORT and DWT most accurate
  cl_methods <- c("CID", "CORT", "DWT")

  df_sils <- compare.silhouettes(df_outcomes,cl_methods,kmin=2,kmax=8,kstep=1,logging=TRUE)

  #plot silhouette trajectories
  df_sils_long <- melt(df_sils,id.vars = c("k"),variable.name="method")
  sil_plt <- ggplot(df_sils_long, aes(x = k, y = value,color=method, group = method)) + geom_point() +
geom_line() +
    xlab("k") + ylab("silhouette width")
  plot(sil_plt)

  #export plot
  saveloc <- paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_","Silhouettes.png",sep="")
  ggsave(plot = sil_plt, saveloc, h = 5, w = 8, type = "cairo-png")
}

# Clustering:
# get k values from silhouette plot
klist <- list("ROI_Commercial" = 3, "Market_share_semi_public" = 5, "EVCS_price_per_kWh" = 5,
"BEV_sales_share" = 2, "CAPEX_gap" = 4)
data_date <- "2018-10-24"

## Clustering with CID:

mthd = "CID"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
```

```
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  # df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])
  # Get already clustered outcomes
  data_clustering_date <- "2018-10-24"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")
  df_cl <- read_feather(path_clusters)

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CID")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with CORT:

mthd = "CORT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"CORT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}


## Clustering with DWT:

mthd = "DWT"

for(kpi in outcomeslist){
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_date,".feather", sep="")
  df_outcomes <- read_feather(path_outcomes)
  cl_methods <- mthd

  # Get clusters for the outcome
  df_cl <- get.clusters.df(df_outcomes,cl_methods,klist[[kpi]])

  #plot clustered time series for one method
  clustered_plot <- plot.timeseries.clustered(df_outcomes,df_cl$"DWT")
  plot(clustered_plot)

  #plot and save clustered time series
  saveloc <-
paste(getwd(),"/Figures/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],"cl.png",sep="")
  ggsave(plot = clustered_plot, saveloc, h = 5, w = 8, type = "cairo-png")

  #export clustering solutions for rule induction in Python
  path_clusters <- paste(wd,"/Data/",kpi,"_",Sys.Date(),"_",policy,"_",mthd,"_",klist[[kpi]],".feather",
sep="")
  write_feather(df_cl,path_clusters)
}
```

```
#adjust working directory
getwd()
setwd("/Users/freekakkermans/stack/Documenten/TU/EPA/MSc_Thesis/Analysis")
wd <- getwd()

#load functions -> Premade functions by Patrick Steinmann have been used. Publicy available through
github.com/steipatr
source("SteiPatr_BBSD_R_Functions.R")

#load libraries
library("feather")
require("ggplot2")
require("GGally")

#load data
outcomeslist <-
list("ROI_Commercial","EVCS_price_per_kWh","BEV_sales_share","CAPEX_gap","Market_share_semi_public")
policy <- "NoPolicy"
klist <- list("ROI_Commercial" = 4, "Market_share_semi_public" = 4, "EVCS_price_per_kWh" = 3, "BEV_sales_share" =
3, "CAPEX_gap" = 4, "BEV_share" = 3)

for(kpi in outcomeslist){
  data_modelruns_date <- "2018-10-15"
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_modelruns_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_modelruns_date,".feather", sep="")
  data_clustering_date <- "2018-10-16"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")

  df_expts <- read_feather(path_experiments)
  df_outcomes <- read_feather(path_outcomes)
  df_cl <- read_feather(path_clusters)

  #get clustering solutions for a given k value
  cl_methods <- c("CID")

  #######pairs plot
  #build dataframe of most predictive parameters (identified through manual analysis of rule induction in Python)
  if (kpi == "ROI_Commercial"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "CAPEX_gap"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "EVCS_price_per_kWh"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "Market_share_semi_public"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "BEV_sales_share"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "BEV_share"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else {    df_expts_red <-
df_expts[c('Progress_ratio_EVCS_cost','ROI_aim_ratio_NWC','Risk_premium_ratio_NWC','Initial_market_share_NWC','lea

}

  #transform clusters to factors for clearer visualization
  df_expts_red$clusterID <- as.factor(df_cl$"CID")

  #plot and save
  pairsplot <- ggpairs(df_expts_red, aes(color = clusterID, alpha = 0.5))
  saveloc <- paste(getwd(),"/Figures/",policy,"_",Sys.Date(),"_",kpi,"-Parameters-PairsPlot.png",sep="")
  ggsave(plot = pairsplot, saveloc, h = 12, w = 12, type = "cairo-png")
}


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# Defined Policies interactions

policy <- "Defined_Policies"
klist <- list("ROI_Commercial" = 3, "Market_share_semi_public" = 5, "EVCS_price_per_kWh" = 5, "BEV_sales_share" =
2, "CAPEX_gap" = 4, "BEV_share" = 2)
outcomeslist <- list("CAPEX_gap")
```

```
for(kpi in outcomeslist){
  data_modelruns_date <- "2018-10-24"
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_modelruns_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_modelruns_date,".feather", sep="")
  data_clustering_date <- "2018-10-24"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")

  df_expts <- read_feather(path_experiments)
  df_outcomes <- read_feather(path_outcomes)
  df_cl <- read_feather(path_clusters)

  #get clustering solutions for a given k value
  cl_methods <- c("CID")

  #######pairs plot
  #build dataframe of most predictive parameters
  if (kpi == "ROI_Commercial"){
    df_expts_red <- df_expts[c('Initial_market_share_NWC',"policy")]
  } else if (kpi == "CAPEX_gap"){
    df_expts_red <- df_expts[c('Risk_premium_ratio_NWC','Initial_market_share_NWC','policy')]
  } else if (kpi == "EVCS_price_per_kWh"){
    df_expts_red <-
df_expts[c('Initial_market_share_NWC','Progress_ratio_EVCS_cost','ROI_aim_ratio_NWC','Risk_premium_ratio_NWC','lea

  } else if (kpi == "Market_share_semi_public"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "BEV_sales_share"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else if (kpi == "BEV_share"){
    df_expts_red <-
df_expts[c("Alternative_technology_introduction_year","Alternative_vehicle_development_speed","Alternative_vehicle_

  } else {df_expts_red <-
df_expts[c('Progress_ratio_EVCS_cost','ROI_aim_ratio_NWC','Risk_premium_ratio_NWC','Initial_market_share_NWC','lea


  #transform clusters to factors for clearer visualization
  df_expts_red$clusterID <- as.factor(df_cl$"CID")

  #add jitter to categorical inputs
  df_expts_red$policy <- df_expts_red$policy + runif(nrow(df_expts_red),-0.3,0.3)

  #Reduce for better visual assessment and to improve speed, picks cases randomly:
  #df_expts_red <- df_expts_red[sample(nrow(df_expts_red), 1200), ]

  #plot and save
  pairsplot <- ggpairs(df_expts_red, aes(color = clusterID, alpha = 0.5))
  saveloc <- paste(getwd(),"/Figures/",policy,"_",Sys.Date(),"_",kpi,"-Parameters-PairsPlot.png",sep="")
  ggsave(plot = pairsplot, saveloc, h = 7, w = 7, type = "cairo-png")
}


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# Policy option interactions

policy <- "Policies"
klist <- list("ROI_Commercial" = 2, "EVCS_price_per_kWh" = 3, "BEV_sales_share" = 2, "CAPEX_gap" = 3)
outcomeslist <- list("ROI_Commercial","EVCS_price_per_kWh","BEV_sales_share","CAPEX_gap")

for(kpi in outcomeslist){
  data_modelruns_date <- "2018-10-24"
  path_outcomes <- paste(wd,"/Data/", policy,"_KPI_",data_modelruns_date,kpi,".feather", sep="")
  path_experiments <- paste(wd,"/Data/", policy,"_",data_modelruns_date,".feather", sep="")
  data_clustering_date <- "2018-10-24"
  path_clusters <- paste(wd,"/Data/",kpi,"_",data_clustering_date,"_",policy,"_CID_",klist[[kpi]],".feather",
sep="")

  df_expts <- read_feather(path_experiments)
  df_outcomes <- read_feather(path_outcomes)
  df_cl <- read_feather(path_clusters)

  #get clustering solutions for a given k value
  cl_methods <- c("CID")

  #######pairs plot
  #build dataframe of most predictive parameters
  if (kpi == "ROI_Commercial"){
    df_expts_red <-
df_expts[c("No_entry_switch","Market_share_cap",'Initial_market_share_NWC','learning_curve_period_EVCS_cost')]
```

```
  } else if (kpi == "CAPEX_gap"){
    df_expts_red <-
df_expts[c("No_entry_switch","Market_share_cap","Market_entry_period",'Initial_market_share_NWC','learning_curve_pe

  } else if (kpi == "EVCS_price_per_kWh"){
    df_expts_red <-
df_expts[c("No_entry_switch","Market_share_cap",'Progress_ratio_EVCS_cost','ROI_aim_ratio_NWC','learning_curve_per

  } else if (kpi == "Market_share_semi_public"){
    df_expts_red <-
df_expts[c("No_entry_switch","Market_share_cap",'Initial_market_share_NWC','learning_curve_period_EVCS_cost')]
  } else if (kpi == "BEV_sales_share"){
    df_expts_red <-
df_expts[c("Market_entry_period","No_entry_switch","Market_share_cap","Shareholder_activation_switch","Alternative_

  } else if (kpi == "BEV_share"){
    df_expts_red <-
df_expts[c("Market_entry_period","No_entry_switch","Market_share_cap","Shareholder_activation_switch",'ROI_aim_rat

  } else {    df_expts_red <-
df_expts[c("Market_entry_period","No_entry_switch","Market_share_cap","Shareholder_activation_switch",'ROI_aim_rat

}
  #transform clusters to factors for clearer visualization
  df_expts_red$clusterID <- as.factor(df_cl$"CID")

  #add jitter to categorical inputs
  df_expts_red$No_entry_switch <- df_expts_red$No_entry_switch + runif(nrow(df_expts_red),-0.3,0.3)
  df_expts_red$Shareholder_activation_switch <- df_expts_red$Shareholder_activation_switch +
runif(nrow(df_expts_red),-0.3,0.3)

  #Reduce for better visual assessment and to improve speed, picks 1000 cases randomly:
  #df_expts_red <- df_expts_red[sample(nrow(df_expts_red), 1000), ]

  #plot and save
  pairsplot <- ggpairs(df_expts_red, aes(color = clusterID, alpha = 0.5))
  saveloc <- paste(getwd(),"/Figures/",policy,"_",Sys.Date(),"_",kpi,"-Parameters-PairsPlot.png",sep="")
  ggsave(plot = pairsplot, saveloc, h = 12, w = 12, type = "cairo-png")
}
```