Exploring the performance and ethicality of various smart charging systems

An explorative agent-based modeling research on the performance, system-usage, and ethical value fulfilment of decentralised and centralised smart charging systems

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Exploring the performance and ethicality of various smart charging systems

Master thesis submitted to Delft University of Technology

in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in Complex Systems Engineering and Management

Faculty of Technology, Policy and Management

by

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To be defended in public on August 28th 2018

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Preface

After completing the advanced agent-based modeling course in my final year of study, I knew I wanted to use this modeling method for my master thesis. During my visit to the graduation market at our faculty I met Tristan, who introduced me to the topic of capturing the societal value of smart energy systems. The integration of smart energy technologies into society has always sparked my interest, and was a major consideration for applying for the energy track. The fact that his research involved the extensive use of agent-based models got me hooked to apply for this thesis opportunity.

This report is a master thesis. It was written as capstone project for the master's program "Complex Systems Engineering and Management" of the Technology, Policy and management faculty at Delft University of Technology. This report is written for those interested in designing smart energy systems, and EV charging systems in the broader sense. It could however also prove interesting for those from other fields, as the report is multidisciplinary in nature.

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Acknowledgements

This thesis marks the final step of my academic career at Delft University of Technology. With a satisfied feeling I will leave the faculty of Technology, Policy and management. The very place that has always felt like home. All that I achieved would not have been possible without the support of others. Within this section, I would like to thank a number of people in particular.

First, I would like to thank Tristan de Wildt for his critical feedback during the development of this thesis. Tristan never hesitated to provide useful tips, question my decision-making, and help me to keep focus on what was the very essence of my thesis. Most importantly, I would like to thank him for the good discussions for which he always took his time despite working on his own research in Canada.

I would also like to thank Emile Chappin for serving as my first supervisor and provide me with thorough feedback on my thesis progress. Emile has already aided me during my bachelor thesis and albeit my many questions, always provided the support I needed. A big gratitude goes to Jan Kwakkel for setting up my EMA experiments and the useful feedback on the experimentation process. The quick experimental execution, which was needed to complete my thesis in time, would not have been possible without his support. I would also like to thank Ibo van de Poel for serving as my chair and his inspiring talks on technology design with respect to ethical values. Ibo helped me to develop a certain recognition for the importance of ethics when designing a technology. Something I have always lacked in the past.

Furthermore, I would like to sincerely thank my friends with whom I have spend all those years at the university. I can only say that we have had a blast! Special gratitude goes to my girlfriend Sue, who has been with me for the entirety of my academic career and has always supported me throughout. Your positivity has undoubtedly worked for the best. Last but definitely not least, I would like to thank my parents, Willem and Yvonne, who have supported me both mentally and financially during my endeavours in Delft. Thank you for the trust you put in me and the interest you posed in my study progress.

Koen van der Veer

Goes, August 2018

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Executive summary

Increased Feed-in of renewable energy sources and an increase of sales of electric vehicles (EVs) complicate balancing of demand and supply. EVs are considered core enablers for dealing with intermittency due to their storage potential. This does however require that these EVs are charged according to smart charging protocols, which is a vehicle-to-grid (V2G) technology. Options exist for designing such a system. However, due to the gathering of personal (transactional) data, and the involvement of monetary assets, ethical concerns such as privacy and trust issues are assumed to arise at or after the introduction of such a technology. This has been the case with for instance smart meters. The effects of such ethical concerns on the usage of smart charging systems are unknown.

The main research question for this thesis is: *"How can a smart charging system be designed which is both used on the short- and long-term and fulfils ethical values of EV owners?"*

The purpose of this thesis was to explore and assess different smart EV charging system designs concerning factors contributing to system performance and possible ethical concerns. The research was conducted by creating an integrated framework of both the capability approach and complex adaptive systems. Agent-based modeling was used as the main research method in order to model the behaviour of EV owners within an smart charging environment. The model aims at providing valuable insights concerning which system design performs best with respect to system performance and ethical value fulfilment. Several architectural design decisions are elaborated on with respect to a decentralised or a centralised system. The research outcomes indicate possible short- and long-term ethical concerns of users with respect to the designed system. The effects of these concerns are at this point unknown, but are considered to have an ongoing effect on the performance of the system.

The research objectives involve the identification of four key architectural design decisions which consist of both decentralised and centralised alternatives. The conceptual framework built upon the capability approach, the unified theory of acceptance and use of technology (UTAUT), and complex adaptive systems is used as conceptual basis for the agent-based model. The experimental design revolves around comparing three experimental design alternatives: a (1) public centralised system, (2) public decentralised system, and (3) a private decentralised system. The public centralised system describes a system which is controlled by a single authority, and in which data is stored within an external database. Furthermore, participants are free to participate. The public decentralised system describes a system which is not controlled by a single authority, and in which transactions are validated through shared consensus. Within the private decentralised system, power is exerted towards a single facilitator, which is authorised to whitelist participants. Aside from whitelisting privileges, the platform is not controlled by a single authority. The combined theoretical framework induces a wide variety of uncertain parameters. Therefore, the experimental designs are explored through an EMA study. The main purpose of this EMA study was to assess the three designs with respect to system usage, system performance, and ethical value fulfilment across a wide range of possible scenarios.

The model outcomes provide knowledge regarding promising design directions as well as directions for further research. The developed model describes the interactions between EV owners and the smart charging platform. The performance of the system is based on three constructs originating from UTAUT. These constructs are: performance-expectancy, effort-expectancy, and social influence. The total performance of the system combined with the personality traits of the EV owners determine whether an EV owner uses the system. Effort-expectancy describes the degree of effort needed to participate on the

platform. Social influence is rooted within the capability approach and incorporates a combination of effects resulting from direct and indirect interaction between EV owners. Electricity is traded through the use of the platform which creates demand and supply. For model experimentation the KPIs for assessment are: the number of system users, the number of transactions, the number of traded kilometers, and the selected ethical values.

Regarding ethical values, the experimental outcomes provide strong indications that a decentralised system scores best on privacy, security, anonymity, and confidentiality. The scores indicate that problems regarding these ethical values are less expected on the short- and long-term as compared to a centralised system. When aiming to design a decentralised EV charging platform, special focus should be placed on achieving trust, as indications are present that trust issues could arise for decentralised systems. Concerning the KPIs related to system usage and performance, the results indicate that a centralised system is highly preferred. For each of the KPIs (number of users, enabled users, number of transactions, and number of traded kilometers), a centralised system scores higher. However, due to the large number of users, centralised systems have high oscillations in demand and supply.

Concerning the main research question, the research outcomes indicate that when designing a smart EV charging system, one should consider both decentralised and centralised design elements. Both elements are needed as solely focusing on either centralised or decentralised systems has implications for value fulfilment as well as system performance. The optimal combination of design elements is at this point uncertain. The research outcomes clearly indicate that extended research in this field is justified. It is important to further identify which system components in both centralised and decentralised systems positively contribute to the chosen KPIs. These components can then be combined in order to work towards an optimal system design. The operationalisation of the capability approach opens new possibilities to assess these combined design alternatives with respect to system usage and ethical values. In that sense, this thesis provides a tool for assessing the designs of smart charging platforms by providing an integrated framework of the capability approach and agent-based modeling.

The research described in this thesis has several implications for designing smart EV charging systems. The capability approach was found to be a proper method for assessing ethical values concerned with the usage of technology. Furthermore, it was found useful to extent the capability approach with other theories and methods such as the unified theory of acceptance and use of technology, complex adaptive systems, and agent-based modeling. Using this approach for assessing smart EV charging systems helps to keep focus on the actual well-being of system users, rather than solely focusing on technological performance. Furthermore, the approach is long-term oriented. Directions for further research are presented. Essentially, these directions stimulate the further exploration of feasible smart charging system designs by extending the scope of design alternatives, further explore the integrated approach of CA and CAS, and further quantify the agent-based model.

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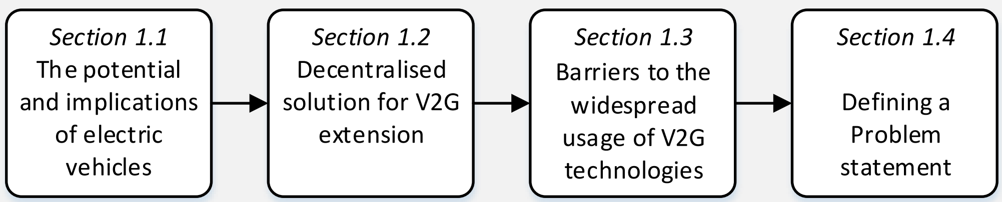
ABBREVIATION	MEANING
EV	Electric Vehicle
CA	Capability Approach
CAS	Complex Adaptive Systems
UTAUT	Unified Theory of Acceptance and Use of Technology
V2G	Vehicle-to-grid
ODD+D	Overview, Design Concepts and Details + Decision-making
CF	Conversion Factor
PCF	Personal Conversion Factor
EMA	Exploratory Modelling and Analysis
KDE	Kernel Density Estimation
KPI	Key Performance Indicator

1. Introduction

Structure

This chapter introduces the topic and the problem statement of this thesis. The starting point of this thesis is the expected storage potential of electric vehicles. Section 1.1 details the potential and implications of vehicle-to-grid integration (V2G). Section 1.2 proposes a decentralised solution for V2G extension in order to increase the storage potential of electric vehicles (EVs). This decentralised solution resides on blockchain concepts and technologies. One of these concepts is *smart contracting*, which is a form of automated transaction protocols. Several of these *smart contracting* technologies are piloted, which indicates corporate interest in the potential of the technology. Section 1.3 defines barriers to the widespread usage of V2G technologies. These barriers are related to the different preferences and abilities of potential system users. This raises uncertainty as to how to ensure that the system is used and remains used on the long-term. This chapter will be concluded by a main problem statement presented in section 1.4.



1.1. The potential of electric vehicles

Increased awareness and concerns regarding the utilisation of fossil fuels and the environment have led to an uprise of renewable energy resources and technologies (Marell, 2014). Addressing environmental problems regarding fuel scarcity and increased sustainability likely involves the increased use of electric vehicles (EVs) (Lopes, Soares, & Almeida, 2011). The increased use of electric vehicles opens up new possibilities and challenges.

1.1.1. Increased usage of electric vehicles

As seen in figure 1, sales of electric vehicles are rising exponentially and will result in considerable impacts on the power grid layout and operation. One of these impacts is the increased load that the electricity system must supply (Guille & Gross, 2009). The increased usage of electric vehicles serves two core functions. First: Transportation has a large share in the world's greenhouse gas emissions (Egbue & Long, 2012). Therefore, the adoption of EVs can provide a near-term alternative that can accelerate the transition towards a sustainable energy system. However, Feed-in of renewable energy sources complicates balancing of demand and supply. Secondly, decentralised electricity storage is considered a core enabler for the energy transition (Römer, Reichhart, Kranz, & Picot, 2012).

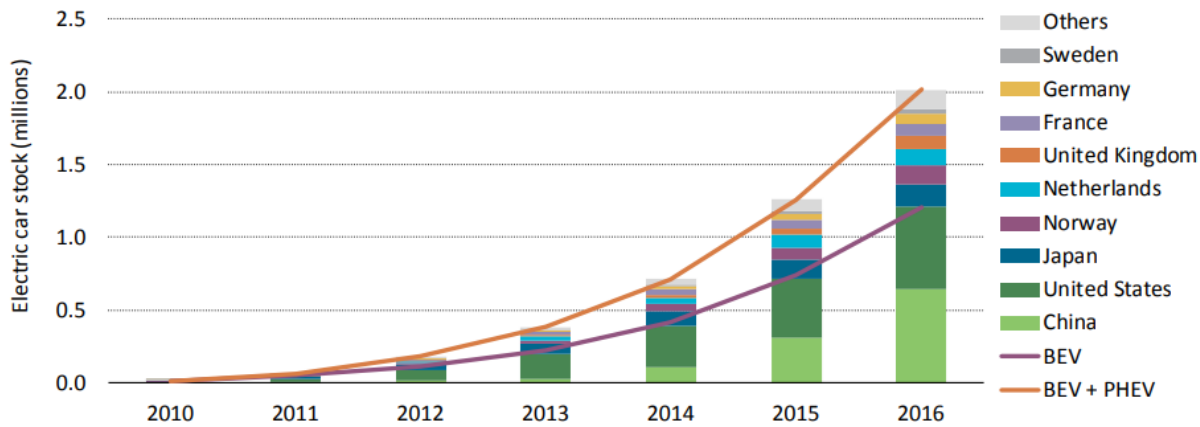


FIGURE 1 GLOBAL EV OUTLOOK 2017 (EV OUTLOOK, 2017)

1.1.2. EVs as storage devices to increase grid stability

Due to the increase of intermittent electricity generation methods such as solar PV and wind, the need for electricity storage increases (Kempton & Dhanju, 2006). Vehicle-to-grid (V2G) is a concept of integrating electric vehicles into the grid to unlock their potential as distributed energy resources for both supply and demand due to their fast response capabilities (Guille & Gross, 2008). Chan, Jian, and Tu (2014) stress that in order to increase grid stability, EVs should be charged according to smart charging protocols. These protocols operate concerning the status of the utility grid in order to avoid conventional peak loads. Therefore, V2G enables the storage potential of EVs. The function of EVs gets extended by combining the storage potential of all integrated EVs which increases grid storage capacity, dynamics and strategic benefits as described by Schoenung and Burns (1996). A future scenario is displayed in figure 2: EVs are integrated within the electricity system in which households use electric vehicles for both traveling and energy storage.

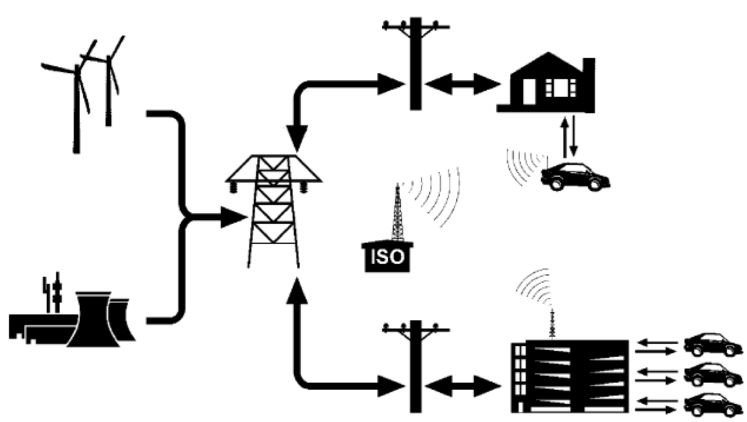


FIGURE 2 SMART GRID LAYOUT

1.1.3. Enabling the storage potential of EVs

Lopes et al. (2011) propose a system which main functionality is to group EVs according to the willingness of owner' to engage in the electricity market. The notion of *engaging* citizens to participate in the market is explicitly acknowledged as a central aspect in the strategy of the European Commission's Energy Union. The European Commission further stresses that vulnerable consumers need to be protected and that citizens have to benefit from new technologies. Private EVs are in use for approximately one hour per day. Leaving a mere 23 hours per day for electricity storage (Kempton & Dhanju, 2006). Kempton and Dhanju (2006) state that: "V2G could pick up the entire electrical load if, for example, only a quarter of the light vehicle fleet had V2G and only a half of those vehicles were plugged in and available when needed."

1.2. Decentralised solution for V2G extension

In order to extent V2G possibilities, this thesis proposes a system, which automatically matches EVs and establishes a transaction between two users. Henceforth referred to as smart EV charging or smart charging platform/system.

1.2.1. Blockchain as a tool for decentralising the electricity sector

A blockchain based transaction platform could pose a solution due to the self-executing nature of smart contracts and therefore transactions can be automatically executed and validated. In essence, the system allows participants within the same system to transact amongst a shared infrastructure without assigning all market power to the platform operator. Furthermore, users should have the possibilities to determine how much and against what price they sell their stored electricity. The assessment of the system places focus on factors contributing to performance as well. Since no such system has been implemented on a large scale, this thesis will serve as a first step in exploring the effects.

1.2.2. Smart contracts to facilitate transactions

Nick Szabo introduced the concept of smart contracting in 1994. Nick Szabo describes smart contracts as "computerized transaction protocols that execute the terms of a contract" (Christidis & Devetsikiotis, 2016). The concept of smart contracts was given new life when distributed ledgers were created based on a programming language supporting the deterministic language of these contracts. The concept was extended and Delmolino, Arnett, Kosba, Miller, and Shi (2016) describe them as "… user-defined programs that specify rules governing transactions, and that are enforced by a network of peers."

Smart contracts allow for multi-step processes between mutually distrustful parties (Christidis & Devetsikiotis, 2016). Three basic concepts underpin a multi-step process: (1) people get to inspect the smart contract code and understand the outcomes of the code before deciding whether they take part, (2) people have certainty of execution. Since the executable code resides on the blockchain, neither party fully controls the code (Frantz & Nowostawski, 2016). Therefore, these contracts operate autonomous and are completely predictable. (3) People get to verify the process, since the contracts are signed with their digital key.

1.2.3. Applications of smart contracts for real-world asset trading

Several applications incorporating smart contracts for sharing of services and property have been rolled-out (Christidis & Devetsikiotis, 2016). *Filecoin* allows devices to rent a certain amount of unused disk space.

Slock is a distributed ledger for opening publically encrypted "locks". It simplified the billing process of opening real-world locks by digital transactions. *Transactive Grid* is experimenting with the concept of a peer-to-peer renewable energy market. Owners of solar panels can sell their excess output through the blockchain to their neighbours with the use of smart contracts.

1.3. Barriers to the widespread usage of V2G technologies

Socio-technical obstacles are possibly as important for the integration of V2G systems, and, due to their ill-definition, harder to overcome (Sovacool & Hirsh, 2009). An important assumption is that a smart charging platform faces similar technical difficulties as other smart energy technologies. Furthermore, when technical problems of such a complex system are resolved, the technology might not be widely used due to the presence of social barriers.

1.3.1. Social barriers for the widespread implementation of V2G concepts

Sovacool and Hirsh (2009) distinguish four core social barriers for the widespread implementation of V2G concepts, namely: "Economic uncertainties, cultural and social values, business practices, and resistance to infrastructural changes." Kirsch (2000) stated that: "The history and sociology of energy consumption suggests that while a few early adopters may assert their individualism, most consumers often remain impatient and close-minded about new energy technologies." They rely on notions of traditions and familiarity. Within their research, Sovacool, Noel, Axsen, and Kempton (2018) conclude that for the successful diffusion of V2G systems, social acceptance, including people's attitudes, perceptions, and drivers is a dominant predictor. The integration of new technologies within society can have unplanned effects. These unplanned consequences should be embedded within the design of new technologies. To this extent, differences between individual EV owners have implications for short and long-term usage of the technology.

1.3.2. Exploring the barriers of a smart electricity technology in practice: Smart metering

To provide a clearer picture of which problems might arise with the implementation of a smart charging platform, smart metering is used as a comparable case. Research on the usage of smart metering technologies have pointed out that apart from technological issues, all kinds of other issues were present. These issues were related to the unfamiliarity of the product, the unproven concept, a low risk tolerance by users, privacy issues, but most importantly, the lack of system usage due to the users rejecting the technology based on ethical concerns (Cavoukian, Polonetsky, & Wolf, 2010).

Zhang and Nuttall (2007) conducted an agent-based modeling study on the adoption of smart metering and found personality traits to have a high influence on the behaviour of potential buyers. Such traits included intelligence, values, experience and general attitudes. Another barrier to widespread implementation of smart metering is rooted within the understanding of consumers (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013). Due to the limited knowledge regarding the functioning and layout of electricity markets, these consumers have a knowledge deficit.

Consumers feel that smart energy technologies result in a decrease of control and apathy (Balta-Ozkan et al., 2013). The monitoring of daily activities was perceived as importunate and created a feeling of discomfort. Furthermore, Privacy issues were raised regarding the monitoring of private lives (Bohli, Sorge, & Ugus, 2010). Consumers expressed concern over external parties gaining knowledge regarding their personal lives and routines. These smart meter readings can be largely mitigated with cryptographic solutions (Bohli et al., 2010). However, the absence of privacy issues doesn't lead to the absence of the feeling of privacy issues by consumers. These privacy issues are largely dependent on the trust these consumers have in the functioning and added-value of the system. This raises questions as to why these users have ethical concerns and why there is a lack of technology-usage. A clear user-centric vision is missing. Egbue and Long (2012) argue for a socio-technical approach. This focus implies that for the design of a technology, ethical issues have to be taken into account.

Marell (2014) argues that besides financial and technological barriers, ethical concerns about e-mobility form a major acceptance factor and are poorly understood. When added-value in terms of societal value is not appropriately designed for, the implementation of such systems raises concerns regarding ethical issues. Research points out that, for this specific topic, it is hard to predict what added-value these systems have and how users are affected by these systems (Oosterlaken, 2012). Attributing to the gap in literature is that research on this topic is very fragmented concerning different types of EVs, different charging systems, different analytical models, and different frameworks and theories.

1.3.3. Ethical issues as barrier of widespread usage

Maintaining privacy on a blockchain based system is hard, caused by the open nature of these systems. All transactions on a public blockchain are openly distributed (Christidis & Devetsikiotis, 2016). This is enhanced by blockchain applications that *monitor* personal behaviour. EV owners have typical driving habits which are indirectly monitored through a smart charging protocol. Two main considerations as to comply with privacy issues exist, namely: 1) Use a new key for each unique transaction. This makes pattern identification more difficult. However, it is more time consuming due to the increased number of key communications throughout the chain. 2) In case of private blockchains, multiple blockchains for different transactions could be useful if other parties gain competitive advantages by tracking participants' activity. Security challenges are present since contracts are concerned with real-life money (Delmolino et al., 2016). Therefore, contracts must be fair-written, ensuring that counterparties are unable to attempt malicious practices for economic gains.

1.4. Problem statement

Section 1.1, 1.2, and 1.3 pointed out the potential of V2G integration as well as several implications when designing a smart EV charging system. Some of these implications are caused by the individuality of the potential system users. An example was found within the implementation of smart metering in which intelligence, knowledge and experience can be seen as personality traits which determine technology usage. Complementing to the problem is that these personality traits are dynamic, i.e. they change over time. Experience and knowledge can increase and decrease over time, changing the behaviour of the user, and causing them to start or stop using the system. Since these traits highly differ between individuals it is hard to determine which system design is most effective regarding these differences between individuals. It is therefore at this point unknown how to determine the best system design to ensure good system performance and high numbers of system-usage.

It is considered most likely that with the implementation of a smart EV charging platform all kinds of ethical concerns arise as well. The users of the system deem these ethical issues important. Therefore, the system design should fulfil these values, ensuring that the users can use the system in a manner they deem just.

The implications are as follows:

- Potential users of the system have different personality traits, which change over time, causing their possibilities, wishes, and demands to change.
- Various ethical concerns likely arise concerning the implementation of the platform.

Resulting in the following uncertainty:

- How to design a smart charging system that is both used on the short- and long-term concerning the differences between EV owners?
- How to design a smart charging system that fulfils possible ethical concerns of users?

The aforementioned combined forms the following problem statement:

Research problem statement:

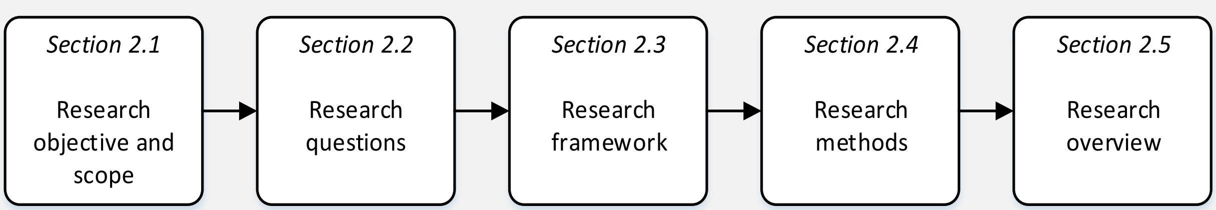
"Due to the differences between individuals, and the multitude of technological design choices, there is a lack of knowledge about the short- and long-term usage of a smart EV charging system and the fulfilment of ethical concerns which consequently results in inadequate knowledge concerning the design of a smart EV charging system."

2. Research approach

Structure

This chapter describes the development of the backbone of the research by presenting a research approach. The research objective and scope are framed in section 2.1. The main research question and corresponding sub-questions are presented in section 2.2. Following the research questions, a research framework which aims at structuring the research is presented in section 2.3. The capability approach and complex adaptive systems theory are introduced as main research frameworks for understanding the problem introduced in chapter one. Viable research methods are presented in section 2.4. Concluding the methodology, section 2.5 introduces the research overview.

Research framework/methods	*Contribution in answering the research question*
Framework: Capability approach	Framework used to incorporate ethical values within the decision-making of people in order to analyse ethical implications of a smart charging system.
Framework: Complex adaptive systems	Framework used to understand and describe the complex behaviour of people used to analyse the performance and ethical implications of a smart charging system.
Method: Agent-based modeling	Simulation technique that allows for the simplistic integration of the specifics of EV owners, allowing for analysing short- and long-term system performance and value fulfilment.
Method: Unified theory of acceptance and use of technology	Theory used to understand and explain the use of technology, by decomposing behavioural intention into prediction factors.
Method: Exploratory modeling and analysis	Approach which uses computational experiments to deal with the high uncertainty of the created agent-based model induced by UTAUT and other concepts.
Method: Literature review	Preparation of conceptual foundation related to smart charging technologies and personal behavioural factors as well as building theory which serves as basis for the modeling study.
Method: ODD+D	Method allowing for a standardised communication of the created model, which facilitates further work on designing smart charging systems



2.1. Research objective and scope

This thesis focusses on exploring the effects on the short- and long-term system usage, system performance, and possible ethical concerns of different design options. The following list of core elements was derived to retain a clear focus throughout the research:

- Subject of interest: short- and long-term performance metrics of a smart EV charging platform
- System of interest: A smart EV charging platform which integrates parts of blockchain technology and smart contracting protocols.
- Implications: Inability to predict optimal system design due to insecure system usage and possible ethical issues.

2.1.1. Research objective

The main research objective is to identify which design choices have a positive effect on the number of users, value fulfilment, and system performance. These design choices should concern the differences between EV owners and the possible ethical concerns that arise after system implementation. Due to the complexity and dynamic behaviour of the system, the adaptive behaviour of EV owners, and personal differences between individuals, agent-based modeling is presented as the main research method. An exploratory modeling and analysis approach is proposed to give insights in the effects of different design options regarding usage and value fulfilment in general across a wide variety of possible scenarios.

2.1.2. Research scope

The scope is bounded to the representation of individual EV owners within a demarcated system which involves a smart charging system and the social interaction between system users. The system demarcation is determined by technological scale which goes as far as the technological characteristics presented in chapter three. The social context is limited to the identified ethical concerns, personality traits of users, and the interaction among these users as presented in chapter four and five.

2.2. Research questions

Regarding the design of a smart charging system, focus is placed on two distinct aspects. Firstly, focus is placed on system usage, including factors leading to increased system performance. Secondly, the system should fulfil ethical values of EV owners. When not properly designed for, ethical concerns are expected to arise hampering the integration of the smart charging system. Incorporating both elements, the main research question is as follows:

Main research question:

"How can a smart charging system be designed which is both used on the short- and long-term and fulfils ethical values of EV owners?"

In order to answer the main research question and concerning the implications introduced in chapter one, a set of sub-questions has been formulated which will be answered separately throughout the research. Their combined insights should aid in answering the main research questions. The sub-questions are as follows:

1. Which technological design options exist when designing a smart charging platform, and which ethical concerns arise when these design options are implemented?
2. Which individual personality factors contribute most to the differences between individual EV owners?
3. How can a model be developed, that gives insights in the short- and long-term effects of different design options regarding the fulfilment of ethical concerns and technology-usage?
4. What can be concluded when comparing different design options?

2.3. Research framework

The main research framework consists of two theoretical concepts. First, the capability approach (CA) is presented as a capable approach for analysing how the actions of users within the system come to be, and how these actions are related to ethical values. Secondly, the system will be looked upon as a complex adaptive systems (CAS). A link is presented between the elements in the system and the specifics of CAS theory.

2.3.1. Capability Approach

The capability approach (CA) first introduced by Sen (1993) is chosen as the main framework used to identify the behaviour of potential system users. The CA focusses on a person's ability to achieve valuable functionings and relates this to a person's advantage (Sen, 1993). In that sense it emphasizes the individual capabilities of people to decide on their own what's best for them. Robeyns (2005) describes the CA as a normative framework useful for evaluating and assessing a person's well-being and social arrangements, social change, and policy design. Regarding this thesis, it is considered a personal challenge to quantify and apply this normative framework.

The CA is primarily focused on the notion of *functionings*. Functionings are the various things that an individual can achieve in life. These functionings are the outcomes from choosing from a set of capabilities. The capability set incorporates the different combinations of functionings a person can achieve. Within this research, the CA will be used as a tool for conceptualising the user-technology interaction helpful for the design of technical artifacts. The framework will help to incorporate ethical values into design.

Theory on the capability approach

A person has certain means which serve as input for capabilities, for instance income or a certain good or service being available. These goods and services can be used to achieve a certain functioning (Robeyns, 2011). However, whether a person can use these goods or services is highly influenced by personal, social, and environmental conversion factors, such as intelligence, public policies, and geographical location. The set of goods and services which a person can and wants to use determine the capability set of this person, i.e. the set of opportunities to achieve a functioning. The person can choose from this set of capabilities, based on personal history, experiences, and preference.

The capability approach places focus on the underlying concerns and values which guide the process of decision. People may deem some functionings important and other negligible based on these concerns and values. These underlying concerns and values determine the individual conversion factors as well as the choice preference of a person (Sen, 1993). The freedom of leading different types of life is detailed in the different capabilities of a person. Figure 3 details a basic overview of a person's capability set and the mechanisms key in the capability approach. This figure is based on the representation of a person's capability set, social- and personal context as developed by Robeyns (2005).

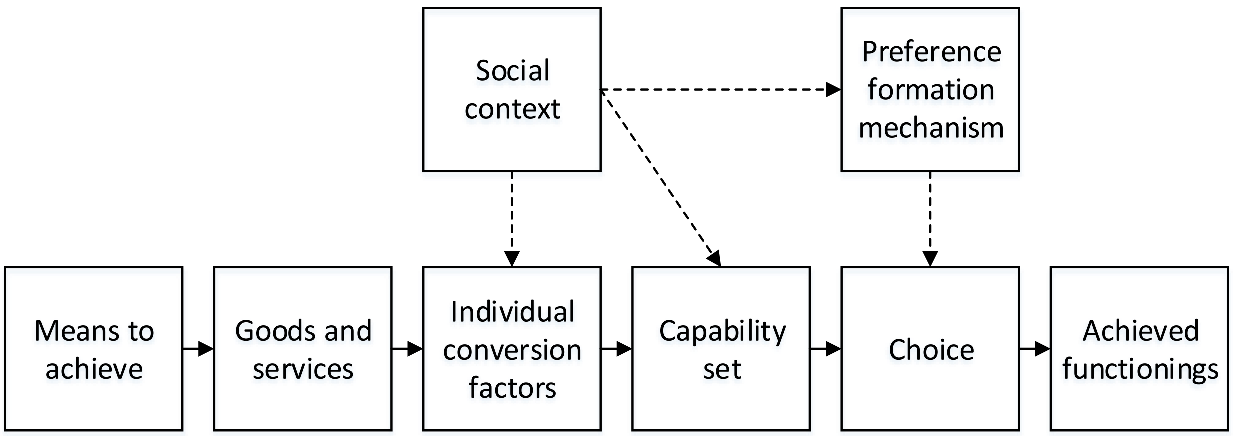


Figure 3 Basic overview of capability approach conversion based on Robeyns (2005)

Relation between capability approach and smart EV charging

The capability approach helps identify future problems of implementation related to values of ethical relevance. EV owners decide whether they want to charge their EV and whether they want to sell the electricity that is stored in their EV. Achieving their functioning, *buying or selling electricity,* depends on different personal and social factors (Clark, 2005). More concise: The decision for an EV owner whether and against which terms to sell the stored electricity depends on its personality and its influence from the social environment. The smart charging system aids in the ability for the EV owners to achieve their functioning. It is a good or service which an EV owner can use, based on its individual conversion factors. Which are in turn shaped by a person's social context. The social context incorporates all that which is related to social norms and social pressure. Whether the EV owner decides on utilising the smart charging system therefore also depends on the personality and ethical values of other system users. It is therefore a matter of value judgements (Sen, 1993). The capability approach can be used to include *agency*, which implies that EV owners have unique values, objectives and goals, such as for instance preserving the environment, that surpass or directly oppose their personal well-being (Clark, 2005). This is particularly interesting as it indicates that EV owners might sell their stored electricity based on other values than the once concerned with their well-being.

Moral significance of design details

The aforementioned implies that details of design have a moral significance. We should, as suggested, make sure that moral values are incorporated in technological designs. To that regard, smart EV charging is positioned within the functioning of humans. As opposed to technological efficiency, the general direction is *How to design a smart EV charging platform concerning ethical values of the users*. More technologies do not necessarily increase our freedom with respect to the lives we want to live. The conversion of goods and services into functionings is affected by environmental conversion factors. Hence, the capability approach could prove a useful approach for the proposed problem.

The capability approach does, as a theory, not provide a complete understanding for development. Gasper (2002) argued for a more extensive conception of the personality of people within the capability approach. This conception should incorporate the values and motives that influence the actions of EV owners. Robeyns (2006) supplements this conception by stating that "… the capability approach is not a theory that can explain poverty, inequality or well-being; instead, it rather provides a tool and a framework within which to conceptualize and evaluate these phenomena". *Freedom* as presented in the capability approach cannot be achieved by looking solely at the active choice of oneself (Sen, 1993). *Freedom* is enormously helped by the choice of others, implying a certain interaction between individuals on a system level. Robeyns (2006) Stresses that applying the capability approach to social change requires the inclusion of one or more explanatory theories.

Technical artefact design and human capabilities

A clear link between the CA and technical design is needed in order for the CA to be a viable research framework. Lawson (2010) has proposed that technical artifacts should be included in the CA as a third element of human capabilities. This implies that technical artefacts are expanding the capabilities of people. As Sen (1993) illustrates, all people are equal in possessing a certain technological artefact. It depends on their abilities and disabilities whether they can use this technological artefact. Thus, whether an artefact actually contributes to the capability expansion of a person, depends on the contextual factors (conversion factors) of this person. The CA suggests that these technologies should be assessed with respect to their effects on person' capabilities on the short- and long- term.

Figure 4 represents the concepts introduced by Oosterlaken (2012) and Robeyns (2006). This overview illustrates the dynamics created by individual system usage. It is shown that individual conversion factors are determined by personality traits. These personality traits also determine how an individual's preference is shaped, which ultimately determines whether and which capability an individual chooses. Choosing a capability results in an achieved functioning. It is assumed that this achievement causes changes in the personality of the individual which on its own changes the preference formation and the conversion factors. It is therefore that decisions made at a certain moment in time, can result in different decision in the future, resulting in a dynamic system. Take note that the original capability approach does not go beyond achieved functionings. Achieved functionings are in essence the end-point for evaluating well-being. However, exploring the system of interest requires an expansion of the original capability approach.

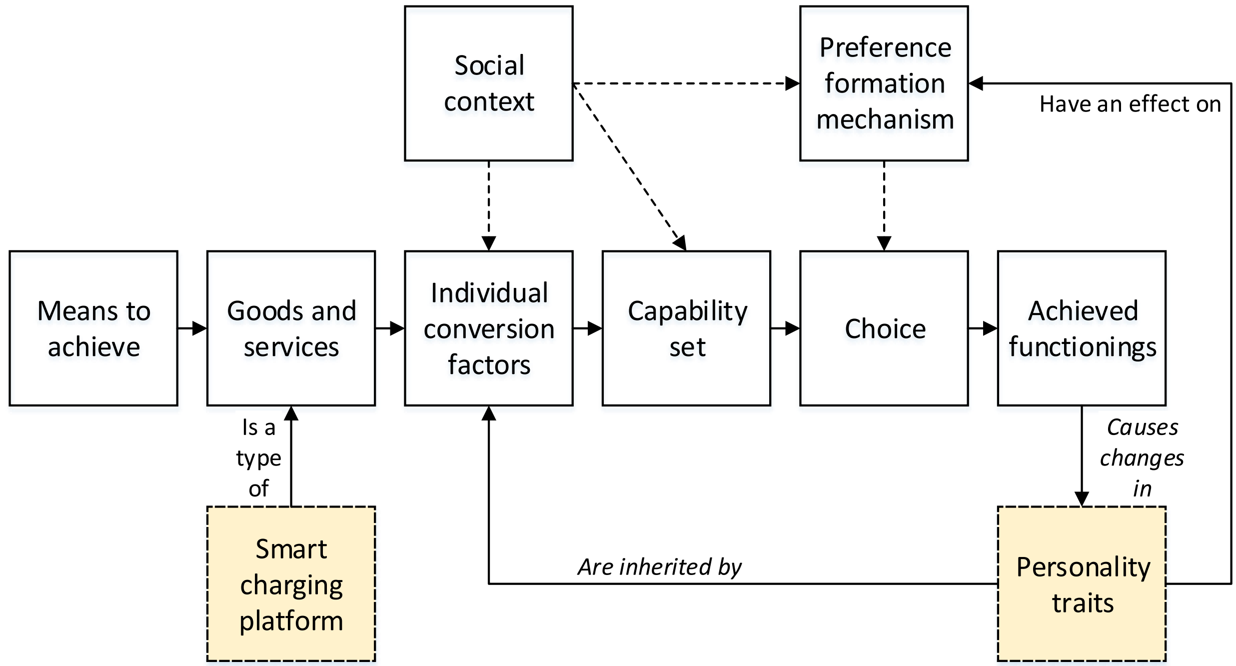


FIGURE 4 MATCHING SMART CHARGING AND CAPABILITY APPROACH

The social context, which is best described as the effects of the individual actions and personality traits of the other individuals in the system, affect these dynamics as well. The social context can, for instance, incorporate the social norms within a system, which some individuals are (unknowingly) affected by. These social norms are established by how other users interact with the system, and what these users experience. The capability approach presents a framework in which individual and social dynamics change the decision making mechanisms of individuals which is useful for assessing their future decisions.

Challenges and implications

The connection between technology and value capabilities is considered dynamic and complex (Oosterlaken, 2012). It is therefore, for practical reasons, not expected to anticipate all capability effects of a technical artefact. The technical and empirical investigations should have focus on the most relevant capabilities, conversion factors and issues for the design challenge. Designing a smart EV charging platform has implications for non-users as well. Increasing the attractiveness of EVs perhaps decreases the attractiveness of conventional cars, decreasing their market value. Such effects are out of scope for this research but are important to reflect on. It is noteworthy that in order to design a product with the intention to increase the well-being of users, the knowledge of how well-being for system users is established, needs to be translated to design requirements, and other technical and non-technical parameters (Oosterlaken, 2012). There are no clear guidelines as to how to achieve this.

2.3.2. Complex Adaptive Systems theory

The description of complex adaptive systems (CAS) as presented by Holland (1992) is widely used for introducing the concept of CAS. Holland (1992) describes complex adaptive systems as systems that involve an evolving structure, i.e. systems that: "…change and reorganize component parts to adapt themselves to problems posed by their surroundings." CAS contain three key features: *evolution*, *aggregate behaviour*, and *anticipation*. They evolve in a Darwinian fashion, improving their ability to survive in their interaction with the surrounding parts. They exhibit an aggregate behaviour which can't simply be derived from the actions of individual parts. The aggregate behaviour emerges from the countless actions of individual components. Lastly, components in a CAS can anticipate the consequences of certain responses and actions. Each part in the system is governed by its own rules. The individual rules of parts can be changed. The rule-based structures of all parts determine the evolutionary procedures that shape the way in which a system adapts to changes in its surroundings. The following two sections discuss why the proposed system can be looked upon as a complex adaptive system.

Smart EV charging as a complex system

The proposed problem is positioned within the system of smart EV charging. Smart EV charging is considered a system as it consists of multiple components, which are not independent. Alterations in parts of the system have an effect on other parts of the system. The electricity grid, smart contracting platform, EVs, and EV owners can be considered components within the system of interest. Due to the presence of different EV owners within the aforementioned system, different entities with different personalities exist. EV owners therefore widely vary in individual decision criteria. This leads to system behaviour being hard to predict based on the complexity of relations between components as well as the individuality of EV owners (Holland, 1992). The individuality of EV owners result in parts of the system being conditioned in different ways. EV owners act according to personal preference and different values they deem important. The consequences of system interaction are therefore hard to anticipate. Therefore, the system is considered as a complex system.

Smart EV charging as an adaptive complex system

Aside from being a complex system, components within the system adapt their individual states and protocols according to their social experiences (Holland, 1992). Sen (1993) has in part developed the capability approach as answer to the dynamics of decision making. Individuals adapt to new situations and develop other or new decision making mechanisms. This is rooted within the notion that the smart EV charging system affects individual EV owners as presented in the framework of Oosterlaken (2012) These EV owners are considered as adaptive agents within CAS theory (Brownlee, 2007). Each EV owner is governed by its own rules determined by their own individuality. They individually decide whether to sell or buy electricity to charge their EV. This notion of individualism of components is key in the definition of complex adaptive systems as proposed by Gell-Mann (1994). Each rule and decision may influence the outcome and the actions of other parts (Holland, 1992).

Considering the system specifics as stated above, the system of interest is considered a complex adaptive system. From the viewpoint of CAS, values and motives fit within the uniqueness of EV owners. It does however assume that agents act and react among each other and with the environment. According to the capability approach and due to the nature of smart contracts, this interaction is mostly indirect.

2.4. Research methods

To help understanding the complexity of interactions and their effects within the smart charging environment, a suitable research method has been defined. Agent-based modeling is a promising method for gaining insights in the effects of user-technology interaction. The capability approach in that sense serves as a tool for conceptualising the ways in which system-users interact within the system, and how they are externally and internally affected.

2.4.1. Research method: Agent-based modeling

The decision-making of people in order to reach an achieved-functioning is considered highly complex. As such laboratory experiments are unsuitable to analyse complex human behaviour within complex decision-making environments (Jager & Mosler, 2007). As the degree of control remains an important issue, simulation modeling provides an alternative. Modeling is applied to include the core elements of the system in order to create an understanding of the complex interactions.

Agent-based modeling is selected as the main research method to capture the behaviour of EV owners and produce the outcomes regarding system performance and ethical concerns. Several criteria were taken into consideration for deciding on a fitting modeling method. These criteria are elaborated on in order to discuss why agent-based modeling is a fitting method. Agent-based modeling seems an appropriate modeling method for the proposed problem due to enabling the following criteria:

- Within this research, EV owners are described concerning the theoretical framework of the CA. In line with the CA, each EV owner has its own conversion factors. These conversion factors can be interpreted as internal states which determine how an EV owner acts and reacts within the system environment. Within agent-based models, agents have internal states and behavioural rules (Gilbert, 2008).
- The CA mentions that each person has different conversion factors, or different levels of the same conversion factor. For this reason, EV owners are looked upon as heterogeneous. Agent-based models are highly applicable to systems with agents with high heterogeneity, as states can be initialised with different values for each agent (Macal & North, 2010).
- The CA implies that EV owners actively make decisions. EV owners choose the capability they value most, based on their internal preference and states. Within an agent-based model, agents can individually assess their situation and make decisions accordingly (Macal & North, 2010).
- The CA implies both direct and indirect interactions between EV owners. Direct interactions take place through active electricity trading on the smart charging platform. Indirect interactions take place through the social context and changes in the system environment. Within agent-based models, direct and indirect interaction can be simulated (Gilbert, 2008).

Agent-based modeling (ABM) is a modeling method useful for modeling systems which incorporate autonomous, interacting agents (Macal & North, 2010). Agent based modeling is concerned with modeling agent interactions. Both notions are present within the capability approach as well-being freedom and agency. Within the system of interest agents are *enabled* by their individual conversion factors to use the system and they *decide* whether to use the system or not based on their own preferences which are governed by their own individual states and the states of other system users.

Interactions occur among the agents within the system and are governed by the different mechanisms introduced within the capability approach. ABM directly originates from complex adaptive systems and their adaptive and emergent properties. Agent-based models tend to be descriptive, aiming at modeling the actual behaviour of individuals. Within an agent-based model, agents can represent all sorts of things and beings such as people, networks of systems or persons, and technological artefacts. The simple descriptive modeling of actual agent behaviour results in seemingly organized behaviour from a system perspective. A fundamental assumption is that the behaviour of agents can be modeled to a reasonable level with respect to credibility and realism. This doesn't require an agent-based model to be complete.

Agent-based modeling is chosen as the main research method. Mainly because it deals very well with heterogeneity between individuals and enables active decision-making. This doesn't necessarily mean that the other described simulation methods cannot be applied, it is a matter of weighted preference. The familiarity with the simulation method contributes to this decision as well. This section described the system from an ABM viewpoint. Thereafter the purpose of the method for answering the main research question is shortly elaborated on. The method of conceptualisation is detailed followed by the steps for model development. Lastly, potential challenges and implications are mentioned.

Smart charging from an ABM viewpoint

Within an agent-based environment, the owners of electric vehicles (EV owners) are identified as the main agents in the system. EV owners are expected to achieve a particular goal. Which, in the case of smart EV charging, is to charge their EV and gain financial profits by selling non-used electricity. This goal is achieved by reacting on the activities of other platform participants. When participants aim to buy electricity for a certain price, other participant can be incentivized to sell this electricity. In a real world scenario, these EV owners will most likely base their decision on numerous emotional, social, and technical factors. For practical reasons, the action to buy or sell electricity is based on limited rationale, or bounded-rationality, implying that the decision of buying or selling electricity is influenced by a limited number of factors.

When an EV owner is matched to another participant in the system, they establish a smart contract which they both have to comply to. This form of direct interaction results in one EV owner to decrease its stored electricity, and another EV owner to increase its stored electricity. In doing so they establish a portion of the supply and demand within the system. It is expected that the local interactions between the EV owners result in overarching network effects and social influence on other participants. These social influences comprise of sharing knowledge and lowering the barrier of system entry. Furthermore, it is expected that EV owners adapt to the changing internal and external environment. Low demand requires EV owners to alter their standard practices.

Within a smart charging environment, users are expected to act upon their own intentions and optimise their personal needs and wishes. More concise, EV owners make their independent choices. These autonomous actions result in different decisions with different outcomes. It is due to these autonomous activities that EV owners within the system develop their own individuality. In other terms, every EV owner is unique. This *heterogeneity* between EV owners results in unpredictable system behaviour.

With respect to the capability approach two individuals with similar capability sets are, due to their individual differences, likely to end up with dissimilar achieved functionings. As can be seen from the previously presented representation in figure 4, the framework as presented by Robeyns (2005) specifically identifies the act of choice of EV owners. Within the capability approach, human agency is at the centre of the stage instead of markets or governments. The choice greatly depends on the social interactions a person has with its social environment and how this affects its preference mechanism.

An important notion within the capability approach is what Sen (1993) describes as *adaptive preferences*. Desires and abilities of people adjust to circumstances due to changes in the social context. Changes within the social context are highly interrelated with changes within the smart charging environment. It can be deduced that the way the capability approach envisions the interaction within a system is quite similar to complex adaptive systems and therefore the method of agent-based modeling.

The dissertation written by Oosterlaken (2012), contains strong ties with both complex adaptive systems and the capability approach. The most important notions with regard to agent-based modeling are that technologies influence the capabilities of system users on both the short- and long- term. Furthermore, she states that interaction is key within the capability approach. A capability is therefore the outcome of the interaction of a person's capacities (which can be interpreted as states within ABM) and the individual's societal position with respect to other people.

Research purpose

An agent-based modeling approach fits well with the described system. However, the modeling technique should also be suitable for answering the main research question. Reflecting upon the research challenges within this thesis, the agent-based model serves as a tool for:

- Operationalising the capability approach
- Acquiring more insights in the functioning of smart EV charging
- Defining and assessing short- and long- term system usage
- Defining and assessing ethical implications for system users
- Providing insights in system performance

Capability approach as tool for conceptualising ABM

The capability approach will serve as a tool to conceptualise the interactions within the agent-based model. The capability approach is used to identify which data is needed, which interaction takes place on system level and in the system's environment, and which conversion factors contribute towards these interactions.

Model development

Several steps are required to develop the model. First a thorough data collection is needed. This data will serve as input for a conceptual model. The data will be quantified and a model will be formalised. The model will then be transposed to computational code in a software package. Although it might seem that in this thesis, the modeling steps are carried out subsequently, various iterations over these steps were carried out. Macal and North (2005) underline that multiple iterations lead to more detailed agent-based models.

challenges and implications

Implications arise when behaviour of agents is based on assumptions. Conscious choices are required when explicitly modeling behavioural change. Even more so when no universal guidelines have been developed (Filatova, Verburg, Parker, & Stannard, 2013). During the conceptualisation of the model, focus is placed on justifying modeling choices. Due to the specific system of interest, large numbers of model parameters might change model performance. This is especially challenging when the agent-based model is used in real-world decision making. Any recommendations should therefore be based on a thoroughly verified and validated model. With regards to the sensitivity and uncertainty of model parameters, a suitable validation and experimentation method was selected. The induced uncertainty gave way to executing an explanatory modeling and analysis approach for experimentation.

2.4.2. Research method: Unified theory of acceptance and use of technology

Within this research, the unified theory of acceptance and use of technology (UTAUT) is applied. UTAUT is a combination of different elements from eight theories/models of technology use, that aims at predicting behavioural intention to use a technology (Venkatesh, Thong, & Xu, 2012). UTAUT can be used to study technology usage across a wide range of application domains. Within this thesis, UTAUT is used to identify and quantify the behavioural intention of potential users of a smart charging system. UTAUT is used to fill the conceptual gaps within the CA that determine preference formation and decision-making. To fill these gaps the four key constructs from UTAUT are used:

- *Performance expectancy*
- *Effort expectancy*
- *Social influence*
- *Facilitating conditions*

The four constructs within UTAUT are used to identify the social and technological context (Venkatesh et al., 2012). Reflecting on these constructs in light of the capability approach immediately suggests that facilitating conditions resemble the conversion factors of individuals. Performance expectancy, effort expectancy, and social influence remain to impact the behavioural intention of an individual to select a capability which is most valued. This is in line with the description of Venkatesh et al. (2012) regarding the separation of the four constructs. These constructs have been linked to the technology as well as the capability approach to create a conceptual overview of the social and technological context.

2.4.3. Research method: Exploratory modeling and analysis

The defined model contains multiple highly uncertain values which were mainly implemented for balancing and parameter normalisation. Neglecting these uncertainties will most definitely result in evenly uncertain or misleading predictions. It raises questions whether the created model should be used solely for identifying the optimal design, rather than exploring the possible outcomes of different scenarios and technology layouts, implying a shift from a predictive towards an explorative model. Concerning smart EV charging, this would entail the identification of a platform design that produces satisfying results across different scenarios.

exploratory modeling and analysis (EMA) could provide a tool to cope with multiple uncertainties. EMA as an approach, uses experiments in order to analyse complex and uncertain issues (Kwakkel & Pruyt, 2013). EMA provides decision support even when a large number of uncertainties are present, by exploring the consequences of different ranges of these uncertainties and thus multiple scenarios. The shift from predictive towards explorative models implies that EMA is not primarily focused on optimising a system.

The created agent-based model is not based on an existing system. It relies on different notions in modern literature which provides enough information to be exploited in a model. Different assumptions, as for instance the inclusion of UTAUT, further defined the model. The different concepts fail to accurately describe all possible system behaviour, hampering the validation of the model. In simple terms it is a matter of insufficient knowledge. EMA is able to accommodate usable insights even when complete validation is impossible (Kwakkel & Pruyt, 2013). These insights can be further used for new directions of system design, which is needed in order to answer the main research question of this thesis.

In order to execute an experiment in line with the functioning of EMA, a list of uncertainties has been identified which were explored in the EMA study. The main aim was to design an experiment setup that supports valid conclusions but is limited in number of computational experiments (Bankes, Walker, & Kwakkel, 2013). Most uncertainties are multiplier factors used for model balancing and parameter alteration. These uncertainties are given a range over which they have been altered to define the scope for the different long-term scenarios.

Defining the finite sample of scenarios from the large set of possibilities is considered a major issue to be addressed in any EMA application (Bankes et al., 2013). Exploration begins with the main research question: *"How can a smart charging system be designed which is both used on the short- and long-term and fulfils ethical values of EV owners?".* With regards to this question, the exploration should produce information regarding system-users, performance, and ethical implications by initialising a set of different technological layouts, which are explored under different scenarios in which uncertain parameters are altered. In doing so, large numbers of model runs are executed, which consequently produce large amounts of data to be analysed.

2.4.4. Research method: Literature study

Robeyns (2006) and Oosterlaken (2012) separately presented ways in which the CA can be operationalised. In order to create an agent based model, which is the central research method, four core components were identified throughout the thesis. These components needed further definition through studying relevant literature.

1. Possible ethical concerns of EV owners

Ethical motives drive benefits for the environment and society at the expense of self-interest. Research has pointed out that moral motives are significant with regards to the acceptance of smart grid technologies (Toft, Schuitema, & Thøgersen, 2014). Smart EV charging is a smart energy technology. New technologies are expected to undergo known and unknown ethical problems, which results in these systems taking many years to become fully integrated in society (Palm & Hansson, 2006). For the short- and long-term usage of smart energy technologies, these ethical concerns as social drivers were studied.

A selection of possible ethical concerns EV owners might have regarding a smart EV charging platform was derived from literature. Within the proposed framework, these ethical concerns determine the social context of the system. The social context has implications for the capability set of EV owners. The social context is however shaped by individuals in the system as well. The interaction between these individuals create a dynamic social environment having implications for the EV owners themselves as well as the capability sets they inherit.

2. Ethical concerns towards capabilities

In order to achieve a better understanding on how ethical concerns are embedded within the system, a literature study aided in translating these ethical concerns towards capabilities. The technical artefact (smart EV charging platform) expands the capability of EV owners to transact with non-trusted individuals. The ethical concerns have implications for this overarching capability.

3. Conversion factors

The CA mentions the heterogeneity of individuals, implying differences in conversion factors between individuals. A set of conversion factors was selected through analysis of the behaviour of EV owners within a smart charging environment. These conversion factors shape the ability of an individual to achieve the functioning of transacting on a smart EV charging platform. This selection was needed as it not only provides insights in the differences among actors, but allows for the modelling of different agents.

4. Technology specifics

The last step concerns with determining which technological components can be selected in order to create a smart EV charging platform. Different components have different implications for the ethical concerns of (potential) EV owners. The link between these components and these ethical concerns should be clear and manageable. The blockchain taxonomy of Xu et al. (2017) was used to identify the key architectural design elements.

2.4.5. Research method for model description: ODD+D

This research entails first steps towards integrating the capability approach and complex adaptive systems theory for exploring design decisions regarding a smart charging system. To increase the applicability of this framework for future research, a form of description standardisation is applied.

Grimm et al. (2010) argue that the ODD protocol can be used to increase reproducibility and provide a means of standardised communication for agent-based models. This is achieved by providing an overview of the models purpose and main processes as well as the underlying concepts and reimplementation details. Müller et al. (2013) elaborate on a further extension of the existing ODD protocol by focusing on human decision-making. This is in line with the theoretical background of the capability approach implying human agency and the ability to freedom of choice. Appendix D details the ODD+D structure as detailed in figure 5. This structure is used to describe the agent-based model and can be used for future research on the topic of human decision-making within smart charging systems and V2G implementations alike.

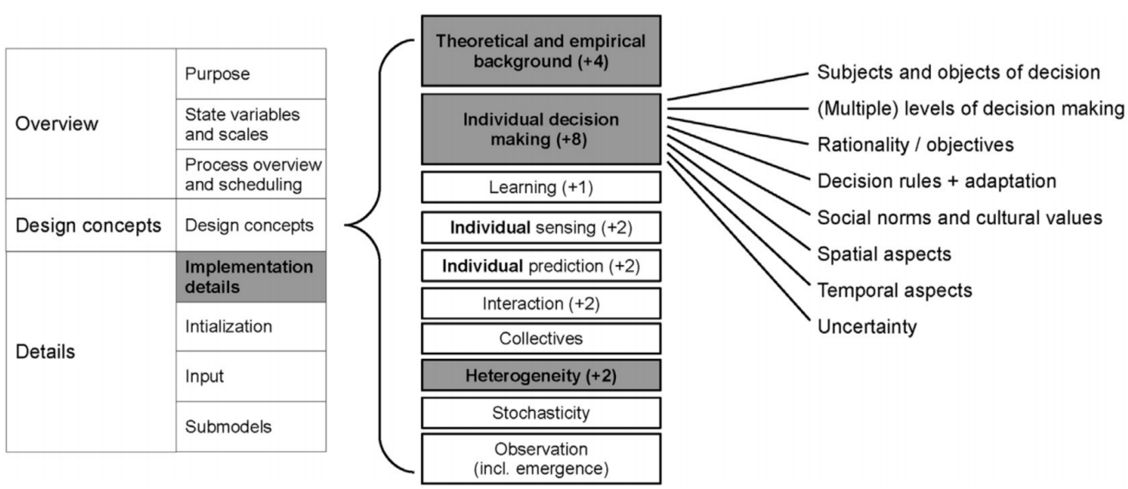


FIGURE 5 STRUCTURE OF ODD+D PROTOCOL AS PRESENTED BY MULLER ET AL. (2013)

2.5. Research overview

The research is conducted over 8 chapters. Chapter one and two have introduced the topic and research framework. Chapter three and four are used to structure the necessary data for modeling the system. Chapter five presents a conceptual model including all related data and model structures. Chapter six details the model experimentation and data analysis. Chapter seven describes important model and research implications and limitations and elaborates on model usage. Chapter 8 concludes this research, reflects on the outcomes, and gives directions for further research. Figure 6 encapsulates these chapters within a research overview.

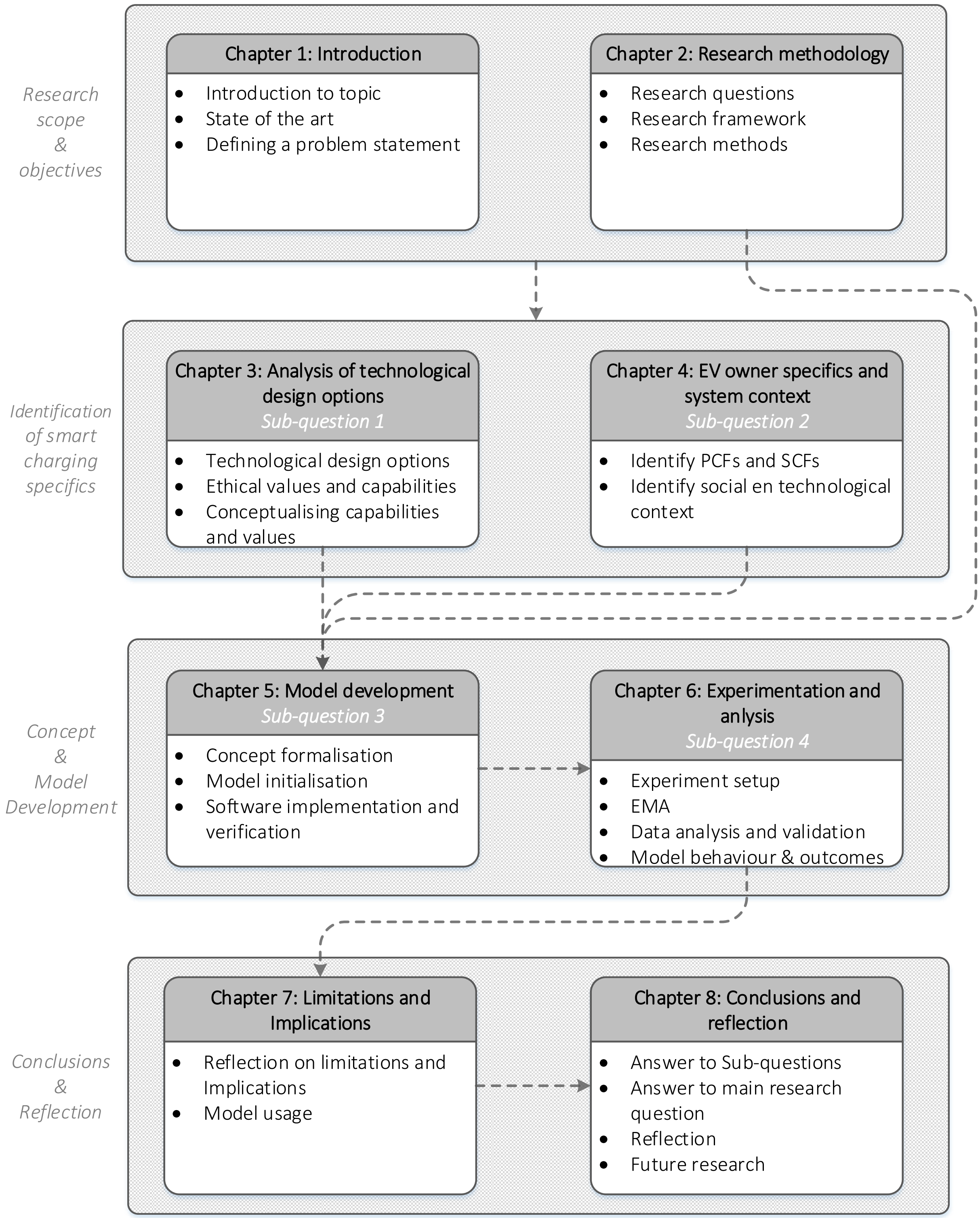


Figure 6 Research overview

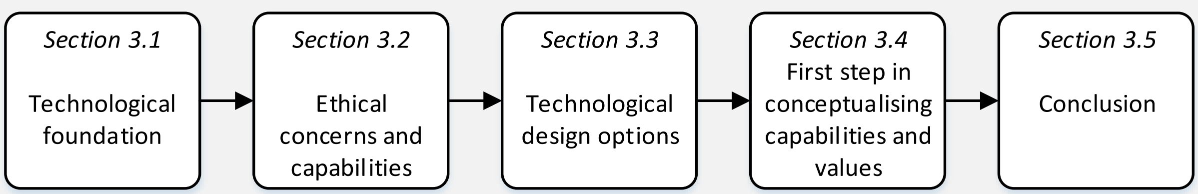
3. Analysis of technological design options

Structure

This chapter details a demarcated overview of technological design options. These design options have been implemented in the agent-based model. The capability approach identifies the possibility of ethical concerns when a new technology is introduced. According to the scope of this thesis, system design should respect two key elements: (1) Which ethical concerns might arise regarding the technological properties of the to be designed system and (2) How can the platform be designed in such a way that it is used on the short term and remains used on the long term.

According to the capability approach, differences between individual people result in different possibilities for people to be able or willing to use a system. Furthermore, personal conversion factors of one person also have an effect on other person's conversion factors, resulting in an interacting environment which changes over time. This chapter elaborates on the technological possibilities for designing a smart EV charging system, with the goal to identify key design decisions as well as which ethical concerns are linked to these design decisions.

Section 3.2 presents the ethical concerns/values which were identified during a literature search on blockchain applications specifically related to transaction platforms. Section 3.3 identifies the key technological design components of a smart EV charging system. The tables presented in this section with regards to the ethical concerns linked to the design decisions are based on the literature presented in those sections. Within section 3.4, the translation of the ethical values towards enabled capabilities is described. Section 3.5 concludes this chapter and reflects on the gained insights and the sub-question associated with this chapter.



3.1. Technological foundation

On a first note, this thesis does not serve as an introduction to blockchain or smart contracting. Deeper insights regarding the mechanisms and concepts available for blockchain implementation are not presented and elaborated on. For the sake of modeling, the key design choices are identified and demarcated. This is in line with the exploratory nature of this research.

3.1.1. Short introduction on Blockchain

Blockchains allow for a new form of computerised transaction platforms, on which trust and transparency are reliably produced (Swan, 2016). It allows for a distributed peer-to-peer network in which participants can form transactional agreements with each other without the need for a trusted intermediary (Christidis & Devetsikiotis, 2016). In other words, trust is placed in the system itself, rather than in a person. Blockchain is commonly associated with cryptocurrencies, which are becoming increasingly mainstream. However, a blockchain has other technological possibilities as well.

Blockchain´s trust mechanism

Since decentralised platforms lack a trusted intermediary, trust is established by using the platform itself (Swan, 2016). Trust emerges as a property from all interactions between the different components on the network. Private and public keys are used to by users to interact on the blockchain. These keys are used to digitally sign transactions. Private keys are used to bring authentication and integrity. Furthermore, they are used to safeguard non-repudiation on the platform by signing transactions.

Validation of transactions

Nodes (participants) in the network validate incoming transactions, through consensus mechanisms, before relaying it any further. This ensures that the transactions on the distributed ledger are valid. Agreed upon transactions are put in order and packed into a timestamped block. These blocks are added to the existing ledger (Christidis & Devetsikiotis, 2016). A suggested block is verified when it contains a valid transaction and references to the correct previous block in the chain.

Facilitating a trustless decentralised platform on a large public blockchain has its downsides. One of these downsides works through in the form of lower transaction processing throughput and higher transaction latency due to energy and time consuming proof-of-work mechanisms. Transactions cannot be executed parallel as smart contracts may contain executables that trigger other smart contracts. Proof-of-work relies on computation to solve mathematical calculations. The computational power to solve these calculations is high, hence the large amount of energy needed. In networks where participants are whitelisted, energy and time consuming consensus mechanisms are less needed, as participants are selectively added to the network.

Blockchain configuration

An important consideration when deciding on implementing a blockchain is whether it is to be a permission-less or a permissioned network. A permission-less network or public network is open for any interested person. This person can participate on the blockchain as a node within the network of already participating nodes (Cachin, 2016). Permissioned networks on the other hand make more sense for participants and facilitators seeking a more controlled and regulated environment with larger transaction throughput (Christidis & Devetsikiotis, 2016). Throughput is increased due to less time needed to validate transactions. Transactions for smart EV charging require a blockchain that supports the account-based model, which enables verifiable multi-step processes, also known as smart contracting.

3.1.2. Short introduction on Smart contracting

Although an established definition for smart contracts remains absent, different definitions exist in modern literature. A modern interpretation is given by Lauslahti, Mattila, and Seppälä (2016), who define them as: "… digital programs, based on the blockchain consensus architecture, which will self-execute when the terms of the agreement are met, and due to their decentralised structure are also self-enforcing and tamper-proof." A more generic and classical definition is presented by Szabo (1997) who states that: "… smart contracts are computerized transaction protocols that execute the terms of a contract."

Implications with parallel execution

Supporting the arbitrary logic of smart contracts has consequences for execution and transaction throughput. The virtual machine (VM) operating the smart contracts cannot tell whether a smart contract will trigger other contracts or affect its internal state (Christidis & Devetsikiotis, 2016). This hampers parallel execution of contracts. When contracts are executed in parallel both contracts could have statements causing changes in either contracts. Therefore, parallel execution of transaction is only possible when there is zero dependency between different contract inputs and outputs.

Distinctive properties of smart contracts

Christidis and Devetsikiotis (2016) assign eight distinctive properties of a blockchain-residing smart contract.

1) The contract has an internal state and different assets can be hold within the contract.
2) Contracts allow for business logic in code.
3) If properly written, the smart contract describes the full range of outcomes of the contract.
4) Establishes data-driven relationships.
5) Is initiated by messages or transactions linked to the address of the contract.
6) Deterministic in nature.
7) Resides on the blockchain, and can therefore be inspected by all nodes.
8) All transactions occur via signed messages.

Entities in the network can engage by establishing contractual commitments with other participants. For a smart charging environment these contracts are automatically created based on personal preferences. A simplified representation of a transaction is showed in figure 7. Alice offers a quantity of asset type X. This is incorporated in the contract, which Alice digitally signs. Bob can accept this offer and sign it with his public key at which points the assets are assigned to Bob. The transaction is later validated through the consensus mechanism.

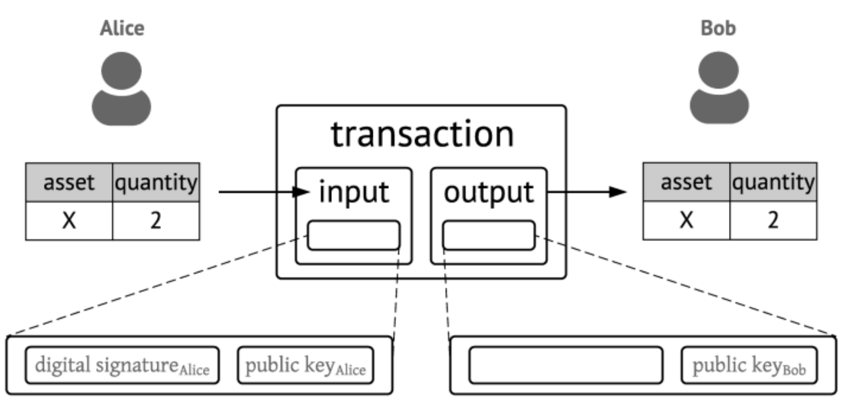


FIGURE 7 SMART CONTRACT FOR TRANSACTIONS (KOSBA, MILLER, SHI, WEN, & PAPAMANTHOU, 2016)

Design and acceptance of smart contracts

Norta (2015) views smart contracts as systems of general complexity due to their non-linear nature, emergent properties and interdependencies. The rationality between components as compared to the parts or the whole is therefore important. Frantz and Nowostawski (2016) believe that due to this complex nature of smart contracts, designing them is difficult and therefore the mainstream adoption and acceptance is limited.

Smart contracts require careful design and implementation. Their nature cannot guard against insecure or ill-written contracts, unless they are automatically written according to predefined algorithms. Ill-written contracts are problematic as the program code is set at contract creation, and can therefore not be changed afterwards (Delmolino et al., 2016). This is solely possible when the contract has an overwriting function hardcoded in the contract. To achieve complete autonomy, the smart contracts may need fail-safe mechanisms written within their code. Frantz and Nowostawski (2016) have proposed a framework for translating institutional specifications in normal language towards machine-readable contract code.

Legal enforceability of smart contracts

Smart contracts have bounded Legal enforceability (Christidis & Devetsikiotis, 2016). Have the smart contract refer to an actual real-world contract is a method to increase the legal enforceability. This process, called *dual integration* deploys a smart contract and records its address in a real contract. The associated real-world contract has to be stored in a safe space. This raises the question whether to use a digitalized smart contract at all, since a real-world contract is created as well. However, real-world contracts can be safely stored in a decentralised manner, retaining the advantages of a distributed ledger (Christidis & Devetsikiotis, 2016).

Security vulnerabilities of smart contracts

Several security vulnerabilities exist in smart contracts based on the Ethereum platform (Atzei, Bartoletti, & Cimoli, 2017). A fundamental cause is found within the high-level programming language used for these contracts. Misalignment between the programmer and the programming language is caused due to the peculiar implementation of code. Another reason is the absence of a self-contained and updated list of vulnerabilities of smart contracts. Security breaches are considered problematic as these smart contracts can be concerned with real-life money.

The terms of the agreement are represented by computer-readable code. Smart contracts are able to confidentially access external data, which can be internally used. Due to the purpose of smart contracts to decrease the number of exceptions and other common errors, the need for a third party validator is removed. The smart contract is placed on the blockchain and no third party is needed to execute the contract, i.e. the contract is self-executing when triggered and the contract conditions are met. For smart EV charging, this would heavily decrease the active participation of the platform users, as contracts are automatically established based on personal preferences. The smart contract is considered secure with regards to its capabilities to prevent unauthorized changes of its internal logic.

3.1.3. Charging infrastructure specifics

As discussed before, connecting EVs to the electricity grid brings new opportunities in terms of the storage potential of electric vehicles. However, the possibilities are limited by the actual limitations of the infrastructure. In order to understand the possibilities of extending the storage capabilities of EVs by introducing smart EV charging, the limitations of the charging network are identified.

For this research, conventional households are considered. Currently most household EV charging is done by a convenience outlet for level 1 (slow or opportunity) charging (Yilmaz & Krein, 2013). The general configuration includes a special charging cord and a wall or pillar-mounted box. For home use, this requires, aside from the power box, no additional infrastructure. The expected power level is 1.9kW for European outlets, resulting in a charging time of just over half an hour per kWh.

Level 2 charging for households becomes viable if these level 2 electronics are prebuilt into the EV. Level 2 chargers can typically charge an EV overnight. Level 2 charging has an estimated output of 19.2kW resulting in a charging time of just over three minutes per kWh. EV owners are likely to prefer the level 2 technology due to it being the faster alternative. Level 2 charging can potentially affect transformation losses (Yilmaz & Krein, 2013). This has impacts on security and economy of developing smart grids. This negative side-effect can be decreased by using a smart-charging protocols and schemas. This implies that the smart EV charging platform should incorporate controlled charging schemas leading to increased grid security and stability.

Controlled charging schemes are possible through electric vehicle management systems. These systems receive and send information to the EV owners and the smart EV charging platform (Mwasilu, Justo, Kim, Do, & Jung, 2014). A type of smart metering system can be included to serve as real-time energy measurement and communications tool. This also allows for bidirectional data exchange for smart contracting optimisation.

3.2. Ethical values and capabilities

Five different ethical concerns were identified. The identification took place by conducting a literature search on which ethical concerns are highly related to smart charging systems and blockchain applications. Undoubtedly more of these ethical concerns exist, specifically related to what users of such applications experience. The selected ethical concerns are further described in this section with the goal of establishing a well founded definition and understanding of both their meaning within this thesis and their distinctions. Some of these concerns are to some extent interrelated and are therefore described in the same section. Section 3.2.1 will elaborate on privacy and security. Section 3.2.2 will describe trust and confidentiality. Anonymity is detailed in section 3.2.3. performance, as a concept, will be shortly described in section 3.2.4. All values will be combined in a conceptual overview in section 3.2.5. Within this section a brief reflection on the relation between the values is presented.

3.2.1. Privacy and Security

Privacy and security concerns are a recurring theme throughout literature regarding the usage of smart energy technologies. Privacy must be taken into account throughout the development phase to ensure that security and privacy are safeguarded. Both Privacy and security are prerequisites for consumer acceptance (Döbelt, Jung, Busch, & Tscheligi, 2015). It is assumed that for using a technology, similar prerequisites exist. These privacy concerns could be a potential barrier hindering the implementation of any IT based system in which user data is collected and distributed. This is even more of a concern when data is transmitted to multiple locations as is the case with a distributed ledger (Anderson, 2007).

It is anticipated that users will work closely with the smart charging utility in order to manage their charging patterns and maximise their economic gains. This requires the users to share data about their energy usage, making them vulnerable for privacy invasions (McDaniel & McLaughlin, 2009). Since their data is stored and utilised among a distributed decentralised platform, the security of this platform itself is essential to safeguard private data from network-borne attacks.

Rodden, Fischer, Pantidi, Bachour, and Moran (2013) found that regarding the users of a system, the issue of privacy was more centered on how companies could potentially exploit the data, rather than that the data was actually monitored. They were concerned about the ways in which the monitoring company might seek financial gains from their data. Depuru, Wang, and Devabhaktuni (2011) additionally state that this data could potentially reveal information about user presence at their residence, at which times they were present, and which in house appliances they often used. The knowledge on presence exposes user habits and behaviour which could be maliciously used by those seeking to mine behavioural data (McDaniel & McLaughlin, 2009).

Regarding the underlying technology of smart contracting (blockchain), users are very concerned about its security (Li, Jiang, Chen, Luo, & Wen, 2017). Research on existing Ethereum contracts, which are based on smart contracting protocols similar to the proposed platform, pointed out that 8833 out of 19366 contracts were vulnerable. This implies that security concerns are justified. Since, monetary transactions are established by smart contracts, security vulnerabilities may lead to financial losses. Furthermore, the tracking of user behaviour regarding financial activities poses infringement on transaction privacy.

Döbelt et al. (2015) conducted a research on the negative effects of privacy concerns regarding smart grid architectures. They specifically mention smart charging of electric vehicles. Consumer privacy and trust were noted as main drivers for the improvement of technology usage.

3.2.2. Trust and Confidentiality

According to Wang and Vassileva (2003)Trust is the "belief in another peer's capabilities, honesty and reliability based on own direct experiences." The ethical meaning of confidentiality refers to the obligation of the data controlling party or system to safeguard entrusted information. Trust and confidentiality are of mayor importance to the introduction of new technologies as they increase shared cognition and the thinking demands of individuals (Mumford & Gray, 2010). (Mayer, Davis, & Schoorman, 1995) details that in order to achieve trustworthiness, a trusted authority should be involved. Since the proposed system is decentralised and revolves around the interaction between non-trustful parties, trust in the system itself is necessary.

Smart EV charging aims at increasing financial gains for the EV owners, whilst utilising the storage capabilities of EVs. The financial gains of EV owners should pose a strong incentive for actions based on self-interest. Trust tends to be lower in systems where parties act in self-interest. Users of smart energy systems tent to distrust the industry and the energy systems governing transactional operations. Goulden, Bedwell, Rennick-Egglestone, Rodden, and Spence (2014) found that users felt distrustful towards organisations which monitored their energy usage and the corresponding loss of autonomy. Negative responses were revoked by the notion of being monitored by energy companies.

Traditional power delivery systems focus on integrity, availability, and confidentiality (Liu, Xiao, Li, Liang, & Chen, 2012). Within these systems trust in the system requires trust in a centralised authority. The described system is based on a decentralised system in which user data is stored and used. This implies an increased connectivity with non-trusted agents. Rodden et al. (2013) therefore rightfully question: *"How much do people trust an active infrastructure given the obvious need to rely upon it for a crucial utility?"* With regards to their research on smart metering, concerns regarding trust were present and users strongly agreed upon the notion that the energy system should be a trustworthy system and were very concerned whether this was achievable.

Verbong, Beemsterboer, and Sengers (2013) state that it is hard to imagine that participants end up trusting external parties with the control over their personal electrical appliances. However, the proposed system contains no external party in full control over such appliances. Different dimensions are related to the amount of system control users have. These dimensions are related to data-ownership, privacy, complexity, and the overall trust these users have in the system. In this way, trust could be established by giving the users the feeling of control over systems that take away complexity while including the opportunity for users to interfere.

An online survey on consumer-driven requirements points out that the majority of respondents pointed out that the energy utility is to be responsible for the storage of their energy data (Döbelt et al., 2015). This utility is to that regard the to be trusted party and should handle this data in confidentiality. However, the proposed system is based on a decentralised platform. The data is stored on the platform and onto the blockchain. According to the survey, consumers were not interested in a responsible authority for data storage but would rather store the data themselves, e.g. *"within a privately owned data server".* To that regard, the platform could create trust since it functions as a data server to some extent. The research clearly pointed out the connection between trust, confidentiality, privacy and the technological artefact. Users commonly noted: *"I don't trust that my data would be treated confidentially if I have to provide it to such a service."*

3.2.3. Anonymity

Propositions in order to protect consumers' privacy often focus on ways to anonymise the data from smart energy technologies (Döbelt et al., 2015). Since smart EV charging collects data regarding charging habits and transactional behaviour, users of the system might prefer to remain anonymous on the platform. Anonymity is closely related to privacy, since it implies the absence of characteristics linked to a person' being. It is for oneself to act without revealing one's identity (Nissenbaum, 1999). With respect to smart contracting, anonymity would imply that transaction contracts are established based on information which is not logically deducible to one's identity. It opens the possibility for EV owners to act or participate while remaining out of reach. Marx (2004) identifies nine personal factors about individuals which potentially reveal identity:

- Individual identification
- Shared identification
- Geographical location
- Temporal
- Networks and relationships
- Objects
- Behavioural
- Beliefs, attitudes, emotions
- Measurement characterisations

Establishing a smart contract requires both users to share at least which data and time the transaction is made. This is established by a timestamp. Grid connection data, which is needed to govern the electricity flow from an EV back to the grid and vice versa, is needed for the platform to operate. This data is linked to a geographical location. Furthermore, if a transaction address is used for multiple transaction, one could deduce transaction behaviour which can be used for identification. Considering the aforementioned, at least three identity revealing information factors could pose problematic for a smart contracting platform.

3.2.4. From a system viewpoint: Performance

The above described ethical concerns are established from a user-viewpoint. The system design is to fulfil the aforementioned ethical concerns on the short and long-term for it to be used by EV owners. However, logically, system performance retains an important aspect for the system designer or operator. The term performance within this thesis relates to identified factors related to the number of transactions and the amount of electricity sold on the platform. Increasing the ethicality of the system might sustain lower values of metrics which contribute to system performance. A trade-off between system performance and value fulfilment is therefore highly likely.

3.2.5. Conceptual overview

A selection of relevant ethical concerns was described in paragraph 3.2. According to these ethical values/concerns, the proposed platform should be designed incorporating the ethical concerns presented in table 1. Take note that the definition of these values within this research are chosen with respect to their ability to be included in an agent-based model. Many definition of values exist and the definitions given are not in anyway regarded as the only suitable definition.

The defined ethical values cannot be looked upon as solitary values. Privacy and anonymity are highly related. Data which reveals ones identity is considered private data. To that extent all information linked to ones identity is related to privacy. However, there is information which is not directly related to ones identity. In order to incorporate this information as well, privacy and anonymity are decoupled. With respect to the agent-based model, privacy relates to the smart charging system's ability to make sure all public data does not reveal private information. Anonymity relates to how the system is able to protect the identity of the participants. Security relates to how easy it is to hack or bypass the protection mechanisms of the system in order to obtain private information or data which reveals the identity of participants.

Trust and confidentiality are also closely related. Trust is related to the functioning of the system. Within this thesis, a system is considered trustworthy when it enables non-trustful parties to safely transact with each other through the smart charging system. Trust is therefore placed upon the functioning of the system as a whole. Confidentiality is more related to the stored data. Confidentiality is achieved through the belief that the system effectively safeguards the personal information.

Ethical value	Relation to subject	Definition within this research
Privacy	Personal information such as transaction data and charging behaviour is stored on the distributed decentralised ledger. This is considered sensitive private information.	The extent to which privacy sensitive information is handled by the smart charging system, and to which extent other participants can access this data.
Security	Infringement of the ledger could leak sensitive private information to be used for criminal activities. This implies that security and privacy issues are strongly linked.	The effectiveness of the smart charging platform to protect against malicious attempts to steal privacy sensitive data.
Trust	The platform relies on transactions between non-trustful parties without a trusted authority in place. Within a decentralised system, trust is established through the functioning of the platform. Within a centralised system, trust is established through trust in the centralised authority.	The extent to which a participant can trust the functioning of the system related to its core functioning.
Confidentiality	The ledger must be designed in such a way that it handles data in full confidence of its users. A decentralised system must safeguard the confidential usage of private data on smart contracts. Confidentiality in a centralised system is highly influenced by the transparency of the centralised authority.	The extent to which a user is ensured that his personal data is only accessible by himself.
anonymity	For the sake of usable and reputable contracts, personal information is stored on smart contracts. This information is to be remained anonymous to ensure unreachability of users. Anonymity and privacy are to that extent highly related.	The extent to which the personal characteristics stored on the system are not explicitly available to other participants.

TABLE 1 OVERVIEW OF ETHICAL VALUES AND THEIR RELATION TO THE SUBJECT

3.3. Technological design options

As aforementioned, this section details an overview of technology components of the smart EV charging platform. This section elaborates on which technological design options are available for system design, and what ethical concerns, as presented in section 3.2, arise when these options are implemented.

The design taxonomy of blockchain applications is used to zoom in on the different options of blockchain design . Xu et al. (2017) present a recently published design taxonomy in which they distinguish four key architectural design decisions. This taxonomy was specially developed for the evaluation and comparison of different blockchain platforms in order to enable research into decision-making frameworks for systems comprising blockchain components.

The design taxonomy was used to identify the technological decisions that can be made when designing the blockchain application for the smart EV charging platform. This taxonomy captures the major architecturally-relevant characteristics of various blockchain configurations. The central design choices are extended by the ethical concerns that potentially arise when they are implemented. The four core design elements are displayed in figure 8.

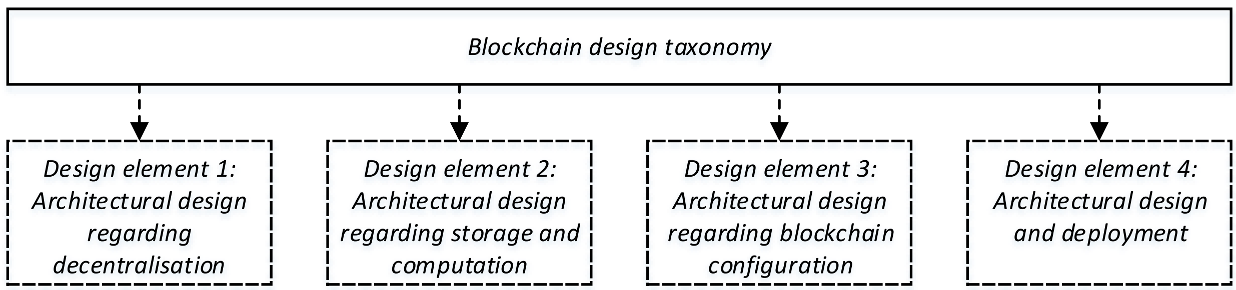


FIGURE 8 BLOCKCHAIN DESIGN TAXONOMY AS PRESENTED BY XU ET AL. (2017)

3.3.1. Architectural design regarding decentralisation

A fully decentralised system includes a permission-less public blockchain. Common examples are the widely known Bitcoin and Ethereum blockchains. These permission-less public blockchains can be accessed by anyone. Users are free to participate in transaction validation, block mining, and undertake transactions. These type of systems need protection against attackers which create anonymous accounts with which they try to manipulate the system. To protect against such security breaches, these systems need more protection by for instance a strong consensus algorithm to validate transactions. On the other hand, fully decentralised blockchains don't require participants to expose their private data to a single intermediary (Catalini & Gans, 2016).

Several researchers including Catalini and Gans (2016) state that verification on the blockchain is *costless*. However, the electricity used to run various consensus protocols have a monetary value nonetheless. Furthermore, retaining a link between products and goods which are not residing on the blockchain, such as electricity, is costly. It often requires protection against asymmetric information and moral hazards.

Two possibilities are identified for a semi-decentralised blockchain. a permissioned blockchain requires an authority which acts as a filter against free participation. This permission can be simple in that it enables users to join the network and to participate. It can also be specific in that it enables a certain user to initiate transactions, or permission to mine. Regulated industries might benefit more from permissioned blockchains (Xu et al., 2017). Anonymity decreases as the authority needs insights in personal data in order to whitelist a participant. This automatically induces trust issues as a third party is to be trusted to handle this data confidentially.

The second option for a semi-decentralised platform entails verification by an external authority. This can be useful in order to evaluate different types of conditions which couldn't or weren't added to the smart contract. This verifier can be considered a third party that is consensually trusted by the participants (Xu et al., 2017). When this verifier is centralized, it potentially becomes a point of failure for all transactions, since they rely on the confidentiality of the verifier. This can be resolved by introducing a distributed verifier. This is done by creating multiple verifiers which are trusted by the whole network. It decreases risk by both increasing the number of verifiers and creating a schema that requires multiple verifiers to accept a transaction. Furthermore, the role of a verifier could also be a human enabled to sign the transaction after another form of validation. It is worth noting that this process can be automated. It is however also noteworthy, that in such a semi-decentralised system, market power is assigned to a single authority (Catalini & Gans, 2016). This raises concerns regarding the trustworthiness and confidentiality of this single authority.

To conclude this section, three alternatives for the architectural design regarding decentralisation have been identified, namely: *fully decentralised*, *semi-decentralised*, and *fully centralised*. A fully decentralised platform has implications regarding security and privacy. A semi-decentralised system has implications concerning trust in the intermediary refraining to the confidential use of private information. According to the taxonomy, the centralised system is most favourable in terms of cost efficiency, but least in terms of fundamental properties. Security issues remain in place since parts of the system reside on the blockchain. A fully centralised system (status quo) is expensive due to the extensive role of the system designer and operator. Furthermore, Trust issues arise due to the increased market power of the system operator. Table 2 presents an overview of the different ethical implications which were stated throughout the literature used in this section.

Design option	*Implications for*					
	Privacy	*Security*	*Trust*	*Confidentiality*	*Anonymity*	*Performance*
Decentralised	+	+	+		++	--
Semi-decentralised	0	+	0		+	0
Centralised	-	-	-	-	-	+

TABLE 2 ETHICAL IMPLICATIONS REGARDING DECENTRALISATION

3.3.2. Architectural design regarding storage and computation

Blockchain networks have limited space available for data storage (Xu et al., 2017). A common practice for the management of user data is to store this data off-chain, implying that an external data server is needed. This means that users can share limited information on-chain using one of four methods. The Ethereum platform provides other methods for data storing. This is achieved by monetizing the data storage.

Two options are available for storing the data on the blockchain itself. The first option is to assign a variable in the smart contract. The costs for storing the data are added to the initial costs for creating a smart contract. The more complex a smart contract is, the more it costs to create a smart contract and to store data on the contract. The second possibility is to store data within a log-event. Smart contract data storage increases flexibility but is also easier to manipulate. It is noteworthy that storing data on the blockchain is a single investment for gaining a permanent storage capacity.

Off-chain data storage is a possibility as well, but requires a direct link between the blockchain and an external data storage facility. This implies that data is to be transferred. Possibilities for external data storage are a third party network or cloud storage. This requires a secure server to be running at all time. The external storage also hampers the immutability of the blockchain. The third party controlling the external storage device has to be trustworthy. Furthermore, security concerns arise due to security of the data is dependent on the external storage device (Tosh et al., 2017).

Computation within a blockchain platform is possible through both on-chain as off-chain methods. On-chain computation is commonly done by executing smart contracts. These contracts are executed when their associated transactions are represented in a new block. Using on-chain computation has benefits with respect to the interoperability between the different systems built on the same network. When a smart contract is properly written, the code is immutable. This facilitates trust-building when the code is shared among untrusting parties. No other alternatives for computing are introduced as the proposed system uses executable smart contracts.

As to the performance of the different storage methods, off-chain storage is highly preferable. This type of storage does not require verification and computation power. Smart contracts are next best followed up by log events which are least preferred. On-chain storage methods safeguard the fundamental properties of blockchain increasing trust, security, privacy and anonymity. An overview of the different ethical implications for data-storage design decisions is presented in table 3.

Design option	*Implications for*					
	Privacy	*Security*	*Trust*	*Confidentiality*	*Anonymity*	*Performance*
On-chain smart contracts	+	+	+	+	+	-
On-chain log event	+	+	+	+	+	--
Off-chain data storage	-	-	-	-	-	++

Table 3 Ethical implications regarding storage and computation

3.3.3. Architectural design regarding blockchain configuration

The scope for applying a blockchain platform determines which configuration is most applicable. Public blockchains are essentially accessible by anyone. It enhances information transparency and auditability but relies on encryption of personal information to ensure data privacy. Therefore, the privacy of data and the limited scalability of public networks are common points of criticism (Xu et al., 2017). Scalability refers to the ease of use regarding the future expansion of the platform. Furthermore, privacy is limited on public blockchains. New participants can freely join the platform and can potentially access personal data of participants.

A number of pre-authorised participants have control over consortium blockchains. In a private network, users of the blockchain are kept within one organization. Permission management systems are needed to authorize participants within the blockchain network. These systems are to be trusted to handle personal data confidentially. Private networks, which are controlled by a single facilitator, are most flexible with respect to the network configuration. Table 4 sums up the different ethical implications regarding blockchain configuration.

Design option	*Implications for*					
	Privacy	*Security*	*Trust*	*Confidentiality*	*Anonymity*	*Performance*
Public	+	+	++	+	+	-
Consortium	+	-	-	-	-	0
private	-	-	--	+	+	+

Table 4 Ethical implications regarding blockchain configuration

3.3.4. Architectural design regarding consensus protocol

Without delving too much in the technological understanding of consensus protocols, a number of viable consensus mechanisms is presented and reflected upon in the light of possible ethical concerns.

Deciding on the consensus protocol heavily impacts the security and scalability of the blockchain platform. Various consensus protocols exist. Proof-of-work is a mechanism of encryption solving which uses a lot of electricity due to the usage of computational power needed to solve the encryption. Proof-of-stake is an alternative to the proof-of-work mechanism. Proof-of-stake is much less costly due to less computational power is needed for the mining process. The byzantine fault tolerance as consensus protocol is commonly integrated in permissioned blockchain. It is a more conventional approach of achieving consensus on valid transactions. The procedure requires all participants to reach consensus on the listed participants of the network.

As mentioned above, the protocol configuration has effects on security and scalability. Double spending, which is a phenomenon in which a competing fork of blocks is bypassing the most recent created blocks, has to be prevented. Methods to surpass this intentional activity are based on selecting the maximum accepted amount of risk.

Proof-of-work and proof-of-stake are typical consensus mechanisms used for public blockchain platforms. They convey excessive electricity inherent to the nature of the consensus mechanism, which requires participants to solve complex puzzles. Byzantine fault tolerance is a consensus mechanism applied to permissioned blockchains (private or consortium). It requires participants to agree on a list of network participants.

In terms of performance and transaction costs, a system which only requires a byzantine fault tolerance consensus mechanism is highly preferred, as it doesn't require high computational power (and thus electricity) to run verification of transactions. Proof-of stake has the highest fundamental properties with regards to trust, privacy and an individual's anonymity on the blockchain. Table 5 Provides an overview of the different ethical implications associated with the consensus protocol design decisions.

Design option	*Implications for*				
	Privacy	*Security*	*Trust*	*Anonymity*	*Performance*
Proof-of-work	++	++	++	++	-
Proof-of-stake	+	+	+	+	+
Byzantine fault tolerance	0	0	0	0	++

TABLE 5 ETHICAL IMPLICATIONS REGARDING CONSENSUS PROTOCOL

3.3.5. Design overview

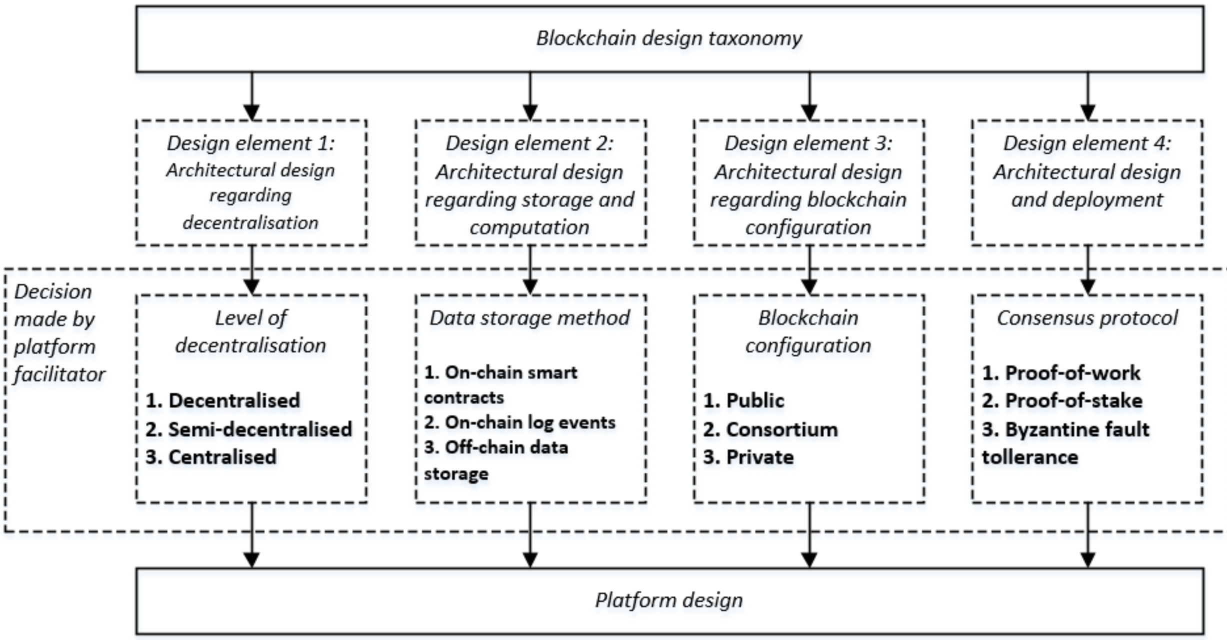


FIGURE 9 BLOCKCHAIN DESIGN TAXONOMY BASED ON XU ET AL. (2017)

Four design options were identified. For each design option, three alternatives are considered. With the number of alternatives for each design element, a total of 81 different assemblies of design are possible. Each design alternative has different implications regarding values of ethical importance. Figure 9 presents an overview of the different design options and alternatives. A total of five ethical concerns were commonly mentioned in literature regarding the four design options. These ethical concerns were: privacy, security, trust, confidentiality, and anonymity. The technological implications on these ethical concerns differ per technology assembly.

3.3.6. Trade-off between values and system performance

As presented in this chapter, the ethical values are to some extent intertwined, interrelated and design decision might hold opposite effects on different values. Furthermore, as stated, it is expected that increasing factors contributing to system performance might cause friction with certain ethical values. The notion of designing a system in order to fulfil *all* ethical values (optimal design) is therefore perhaps not viable. Possibly, a trade-off between certain values has to be made in order to achieve the most desired system design. Value trade-off is difficult since it is hard to define a common unit for value measurement (Hadari, 1988). It is even more complicated since each individual differs in value judgement. However, these trade-offs are perhaps necessary to make decisions when multiple values are at stake (Keeney, 2002). In order to establish a ground for comparison, the ethical values were included in the basic capabilities of transacting on the platform. In doing so, designs can be compared related to the enabling of these capabilities. Accessing all value trade-offs will concern a 6-dimensional (6 values – 1 value per axis) value judgement framework. Logically this is not representable by a graph and is to complicated to envision. Therefore a scoring mechanism will be used to transpose the fulfilment of values towards a score. The scores will be equal for each experimental setup.

3.4. Conceptualising capabilities and values

To conclude this chapter, the selected ethical concerns/values have to be placed in the light of the capability approach. The capability approach assures that all capabilities in a capability set are accessible by people (Robeyns, 2005). Thus, when selecting a most valued capability, these people should be able to consider all capabilities at their disposal. However, in a real world situation, two persons with an equal set of capabilities will most likely achieve different functionings, as they convey their actions based on different preference mechanisms and values. To this extent the differences between people result in different outcomes for identical capability sets. It is assumed for this study that people poses identical commodities which are the basic needs to acquire the achieved functioning of transacting with other EV owners on the smart EV charging platform. In other words, people have the same capability set related to smart charging. Whether they achieve this functioning depends on different personal and social factors called conversion factors, such as for instance knowledge regarding the system. These conversion factors represent the uniqueness of agents in the system. These will be separately described in chapter 4.

Sen's framework is flexible and enables a large degree of personal interpretation, allowing for application and development of the framework in many different ways. Most important for this research is that there is no fixed or finite list of capabilities. Selecting capabilities depends on personal value judgements (Robeyns, 2006). Agency, which recognises the individual goals and values of EV owners is to that regard included in the capabilities of EV owners. Therefore, regarding the scope of this research, a selected list of capabilities is identified.

When reflecting on the capability of an EV owner to *transact with other EV owners on a smart EV charging platform* it seems rather simple to achieve this functioning when all commodities are available. However, it is assumed that five ethical values could potentially be violated when EV owners start using a smart charging system. Therefore the capability to transact on this platform is extended with the five ethical values to become the capability to *transact with other EV owners on a smart EV charging platform in a secure, private, anonymous environment ensuring confidentiality and trust in the system.* One could consider that all these values need fulfilment before a user will use the system. However, it is expected that trade-offs are needed between ethical value fulfilment and factors contributing to the performance of the system. Since all ethical concerns are evaluated as being equally important, the decision was made to regard each ethical value as a standalone factor influencing the capability. In doing so, the assessment of which capability is better enabled by which technological design becomes possible.

The decision of considering each ethical concern within separate capabilities is discussed. Clark (2005) states the possibility for capabilities to be evaluated in terms of a diversity of options. This implies that for the essential capability of transacting on the platform, a diversity of options are possible. This is combined with the framework of Oosterlaken (2012) which is presented in figure 10. This framework implies that the ethical concerns can be inherited into the capabilities of people. The portrayed social network/system can be interpreted as the combination of all socio-technical aspects concerned with smart EV charging. The concept is based on the notion that technical objects cannot be understood in isolation (Oosterlaken, 2012). A new technical artefacts potentially leads to new ethical concerns associated with this technology. These ethical concerns translate to changes in the social network or system; for instance a change of social norms or what people generally value. These changes give further meaning to human capabilities.

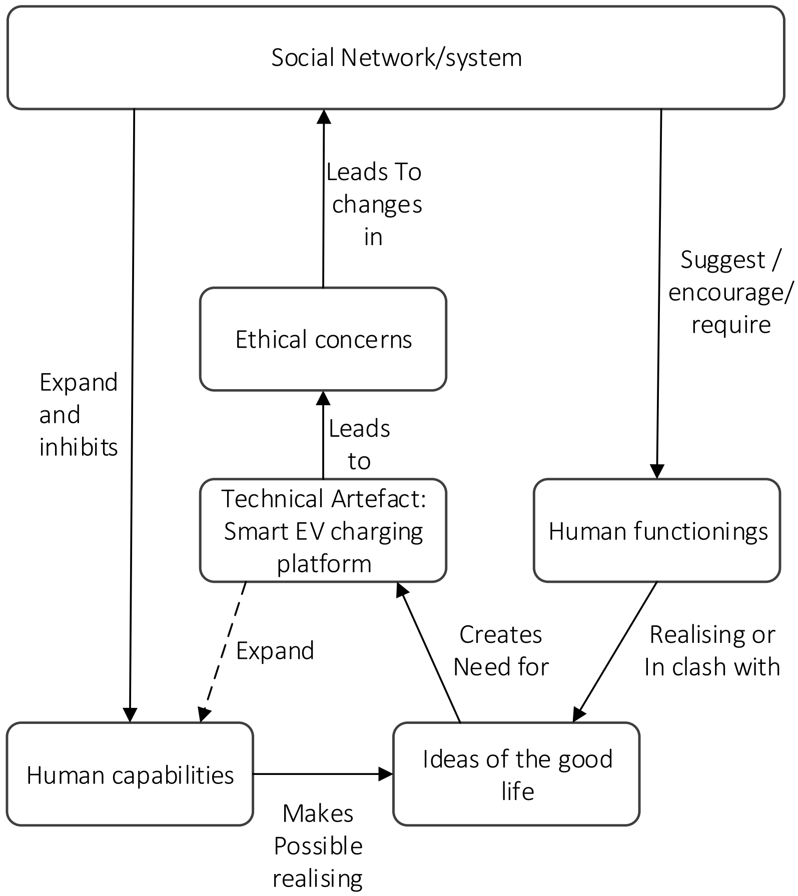


FIGURE 10 VALUE CAPABILITY FRAMEWORK DERIVED FROM OOSTERLAKEN (2012)

The following diversity of capabilities was logically derived:

- Transacting on a *secure* smart EV charging platform
- Transacting on a *privacy*-enabled smart EV charging platform
- Transacting on a *trusted* smart EV charging platform
- Transacting on a *Confidential* smart EV charging platform
- Transacting *anonymous* on a smart EV charging platform

Related to theory on the capability approach, this decision is partially in line with the distinction between basic, internal and combined capabilities as detailed by Nussbaum (2000). The five diverse capabilities as presented could be viewed as basic capabilities to reflect the development of more advanced capabilities. Moral concerns are represented by the ethical values incorporated in the above mentioned capabilities. The combined basic capabilities are definable internal capabilities which can be combined with suitable external conditions to acquire an achieved functioning. The internal capability would then be to transact on the smart EV charging platform while safeguarding all five ethical values as presented in this chapter. By viewing the ethical concerns within basic capabilities, the fulfilment of all five values at the same time becomes less needed.

3.5. Conclusions

Research sub-question 1:

“Which technological design options exist when designing a smart charging platform, and which ethical concerns arise when these design options are implemented?”

Regarding the design of a smart charging system, four core design elements were identified:

1. *Level of decentralisation*: Describes the extent to which a single authority has control and power over the system. Three design decisions are taken into account. These decissions are related to whether the system is to be (1) centralised, which includes a single authority with extended power and control, (2) semi-decentralised, describing a system which is partly controlled by a central authority, but has other parts decentralised or is (3) fully decentralised, entailing a system that has no single authority controlling any parts of the system.

2. *Data storage*: Describes the way in which private and transactional data related to transactions on the platform are stored. Three data-storage methods were chosen. On-chain data storage is possible through smart contracts and log events. Data is stored on the distributed ledger by computer readable code on a secured smart contract. Off-chain data storage is possible through an external data storage facility.

3. *Blockchain configuration*: Revolves around decisions associated with the accessibility of the platform. Three design options are taken into account. The first design option entails a public blockchain platform. This type of platform is freely accessible by any person who wishes to use the platform. Secondly, consortium blockchains assert a certain amount of power towards a selected group of peers, which decide whether new participants can enter the platform or not. Thirdly, private platforms concern a single point of authority which decides on who participates and how transactions are verified and written.

4 *Consensus mechanism*: Three consensus mechanism are taken into account: proof-of-work, proof-of-stake, and byzantine fault tolerance. Since no authority controls the information of participants, consensus should exist on the distributed ledger on which all transactions and data is stored. Different consensus mechanisms exist to safeguard that all participants in the network collectively agree on the contents of the ledger. Each consensus mechanism differs concerning performance, costs, and flexibility.

Regarding literature on the development of blockchain platforms and the blockchain taxonomy, these components have implications for several ethical values: Privacy, security, trust, confidentiality, and anonymity. These values have been translated to capabilities for further use in the agent-based model.

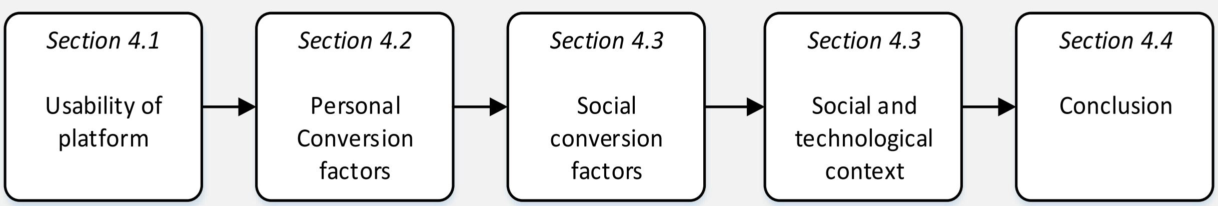
4. Identifying EV owner specifics and the system context

Structure

Chapter three introduced different design elements of the platform and which ethical concerns are likely to occur regarding the design possibilities of smart EV charging. This chapter elaborates on the identification of personality traits (conversion factors). It was earlier mentioned that these traits are needed in order to develop an agent-based model. These traits determine whether the platform is useful for an EV owner. It was already found that these conversion factors differ between EV owners. These differences have to be properly defined in order to effectively model a system in which different actors interact according to different internal states.

The starting point is to understand what factors within a smart EV charging environment determine its usability. These factors are linked to the personality of an EV owner. By doing so, a selection of the most important conversion factors essential in understanding user behaviour in the demarcated system were identified. The output of this chapter is a list of conversion factors as well as a schematic overview of the technology components and how these technology components can be represented in a model.

Section 4.1 discusses which factors contribute most to the usability of smart EV charging, and how these factors relate to the conversion factors of EV owners. Section 4.2 elaborates on this set of personal conversion factors. Section 4.3 details which social conversion factors are at play, detailing the interaction between individuals in the system. Section 4.4 introduces the social context which is created by the differences between EV owners and the interaction between them and the platform. Section 4.5 concludes the chapter by providing an answer to the sub-question related to this chapter as well as giving an overview of the most crucial insights.



4.1. Usability of platform

Different models aim at identifying incentives and barriers of technology usage. Several commonly used ones are: technology acceptance models (TAM), theory of planned behaviour (TPB) and theory of reasoned action (TRA) (Wymer & Regan, 2005). These frameworks can be used in quantitative studies. However, their broad range of theoretical foundations result in a confusing and sometimes contradictory overview of significant variables. Due to the complexity of the system, the confusing concepts of technology adoption, and the limits of this research, a limited selection of usability factors was identified and elaborated on.

4.2. Personal Conversion factors

In this section, the (potential) users of the system are described. This is mainly done by describing the variables in which EV owners differ in the light of the capability approach and complex adaptive systems. The theory implies that the users have different personalities which govern their decision making. The capability approach defines these contextual drivers as conversion factors. These conversion factors can be personal (e.g. skill, physical condition, or intelligence), social (e.g. power relations), and environmental (e.g. climate or geographical location) (Robeyns, 2005).

Note that an extremely large number of conversion factors exist which have an effect on how individuals act. It would be impractical to implement all conversion factors within the model. Therefore, for modelling purposes, a limited selection is made. For modeling purposes, users are to some extent considered equal with regards to normally heterogeneous factors. For instance, Age, religion, and geographical location are not included as heterogeneous factors. This highly decreased the number of conversion factors.

4.2.1. Personal conversion factor 1: Skill

Ramamurthy, King, and Premkumar (1992) have examined user specific characteristics and their link to the effectiveness of technology usage. These characteristics are: domain and system expertise, practical experience, and intelligence. With regards to the usability of smart EV charging, technical skill among users is a significant factor (Witherspoon, 2017). This skill increases or decreases over time according to the complexity of the technology. In essence a new user will increase its skill when using the smart EV charging platform. This increase in skill ultimately increases the usability of the platform. Skill also reflects on other participants as a form of learning-effects. Witherspoon (2017) states that new blockchain platforms are far from standard practice and that therefore skill progression is potentially slower (for instance learning how to interact with the blockchain and smart contracts). Furthermore, the lack or absence of basic skills with regards to using a decentralised platform may hamper initial usage of the system.

Skill is considered as an important conversion factor of EV owners, determining the usability of the smart EV charging system. Refraining to the acceptance or usage of smart energy technologies and smart metering in particular, it was found that skill is a significant factor in ones ability to utilise such technologies (Czaja et al., 2006). It was also found that a higher level of skill led to less anxiety and higher interest in using technologies. Skill represents the extent of familiarity and experience with a system. Having general skill regarding comparable technologies and the role of these technologies determines the possibilities for system use. Furthermore, as was earlier mentioned, learning-effects play a role within an ecosystem with multiple users. Highly skilled individuals reflect this skill onto lower skilled individuals creating a pattern of skill attainment. Therefore, skill attainment is not only generated in isolation, but emerges from social interaction as well.

Taking example of smart metering services, maximisation of potential benefits demanded consumers to hold substantial skill regarding energy pricing (Luthra, Kumar, Kharb, Ansari, & Shimmi, 2014). It is assumed that skill as a conversion factors is a determinant of the usability of smart EV charging. Complementing this, skill will increase due to the usage of the system. Therefore over time the skill of a user increases or decreases depending on whether this user has the ability to use a technology or not. As technology gets integrated within our everyday life, people who are less tech-savvy are more likely to become more distanced and disadvantaged (Czaja et al., 2006).

Due to the complexity of technology and its impact on society, ambiguity towards technology has established. The increased sophistication of technology might stop people from taking part of the implementation of these technologies due to the feeling that they lack the necessary insights (Palm & Hansson, 2006). One way to potentially overcome this phenomena is to increase the usefulness of the human-machine interface.

4.2.2. Personal conversion factor 2: Intelligence

Intelligence is the factor contributing to the ability to acquire technological skill (Czaja et al., 2006). People who have higher levels of crystallised and fluid intelligence are more prone to require skill. The use of technology requires new learning, therefore the extent to which users can use a technology depends on their intelligence. Czaja et al. (2006) found that age and education were correlated with intelligence, implying that they could be represented by a single measure of intelligence. A higher level of intelligence aided in people's ability to use technologies in a more effective manner. Within this thesis, intelligence is therefore perceived as one's ability and speed to adapt to new and complex technologies. This leads to different patterns of technology usage and has implications for the willingness of users to participate on the short- and long-term. Ramamurthy et al. (1992) state that the level of intelligence is positively associated with performance. This performance increases over time as intelligence is the main driver for acquiring more system experience, which in term increases the skill of a system user.

4.2.3. Personal conversion factor 3: Individual charging patterns

Individual charging patterns play a significant role regarding the effectiveness of EV charging. Bidirectional smart charging requires two participants with opposite desires. In simple terms, the system works best when one individual aims at discharging and gaining a profit, whilst the other aims at charging against desirable rates. When these charging patterns conflict, the effectiveness of the system decreases and with that the added-value for potential users. As with skill and intelligence, the personal charging patterns determine individual system performance.

Franke and Krems (2013) investigated whether and to which extent individual charging patterns differ. They concluded that two distinct charging groups exist, which they identify as *low* and *high* intensity. Low intensity charging represents individuals which charge their electric vehicle when the battery is close to exhaustion. High intensity charging represents individuals which will charge their electric vehicle at any opportunity. To this extent low intensity charging represents a group of EV users which take full advantage of available battery resources at all times. Individuals with a high intensity charging pattern will most likely fit less in a smart EV charging environment due to their non-strategic behaviour.

Concerning the research by Franke and Krems (2013), users traveled an average distance of up to 38 kilometers a day. On average users were willing and comfortable to drive a fully charged car for 124.9 kilometers before charging. Consequently, in most cases a fully charged car can be left uncharged for multiple days. Individuals with low intensity charging will therefore only charge their cars for approximately three times per week, as compared to every evening for high intensity charging.

A normal distribution of charging intensity between individuals was deemed satisfactory. With its peak at the battery being at 50% charge. Figure 11 Presents the results from an experiment for EV charging and shows two distinct peaks at 15% and 35% charge. These peaks were caused by the warning mechanisms in the EV itself and are therefore not considered as natural behaviour. These warning-peaks are vehicle specific and are therefore not considered within the model.

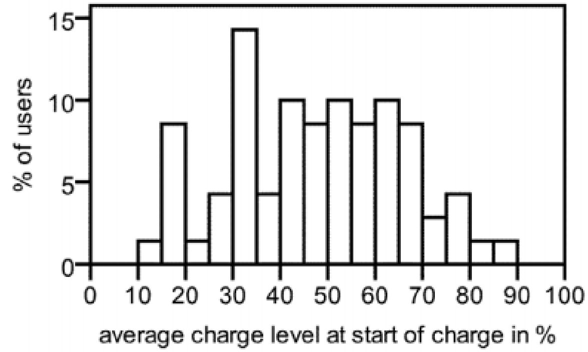


FIGURE 11 EV CHARGING PATTERNS BY FRANKE & KREMS (2017)

4.2.4. Personal conversion factor 4: Daily driving distance

Daily driving distance alongside personal charging patterns determine, to a large extent, when an electric vehicle needs to be charged. Concerning the private driving behaviour of a sample of over 100.000 interviews, a distribution of driving distance was established (Wu et al., 2010). For the user-representation in the model, an exponentially decreasing function is established on the data presented in the research. This function is visualised in figure 12. According to the research, a small portion of EV drivers travels more than 200 kilometers a day. This portion is not represented in the model. The driving distance range is limited to 200 kilometers.

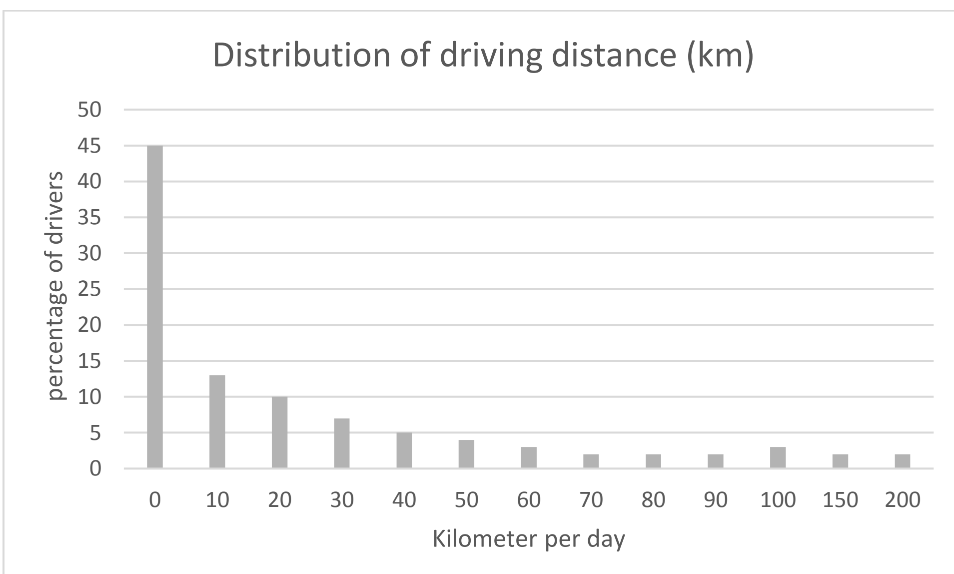


FIGURE 12 DISTRIBUTION OF DRIVING DISTANCE IN KILOMETERS

4.2.5. Personal conversion factor 5: Battery range

More and more built-models of fully electric vehicles are introduced on the market. These vehicles highly differ in battery range. Together with charging patterns and driving distance, battery range determines at which point in time an EV owner will plug in its electric vehicle. Taking into account the 9 most sold electric vehicles as of 2017, on average, an electric vehicle has a range of approximately 270 kilometers. The Tesla model S peaks at 510 effective kilometers, while the Kia Soul closes the fence at 150 kilometers. For the model, it is assumed that the distribution between EV owners is a normal distribution between 150 and 500 kilometers of battery range.

4.2.6. Overview of personal conversion factors

A total of five specific user conversion factors have been identified. These conversion factors represent the heterogeneity among the users. An overview is presented in table 6.

Conversion factor	*Effect on ability to use smart EV charging*	*Implication for smart EV charging*
1. Skill	Higher skill lowers the barrier of utilising a technology. Skill increases over time when a system is used, furthermore social interactions increase the attainment of skill, making the system more usable for an individual.	Higher complexity increases the gap between high and low skilled individuals. Highly complex systems require high initial skill of individuals. This makes the system less useful for lower skilled individuals.
2. Intelligence	Higher intelligence increases the speed at which an individual will attain sufficient skill to efficiently use a technology.	Intelligence increases personal differences between system users.
3. Charging pattern	The incentive for people to charge their car depends on their personality. Some might charge every evening whilst others charge when their battery charge gets below a certain level.	Differences in charging pattern determine the compatibility between different users in the system. An individual's charging pattern determines the effectiveness of the system in its current state.
4. Daily driving distance	EV owners have different daily driving distances.	Daily driving distance determines how fast a fully charged battery is depleted and consequently determines the need for charging.
5. Battery range	Different EV models have different travelling range.	The battery range determines how far an EV owner can drive before the EV charge reaches below an acceptable level.

TABLE 6 CONVERSION FACTORS OF EV OWNERS

4.3. Social conversion factors

The personal conversion factors presented in section 4.2 represent the individuality of EV owners. These values determine the individual behaviour of an EV owner according to internal states. However, these actions are also affected by the states and actions of other EV owners in the system environment. Within the capability approach, these social interactions are known as social conversion factors. They are factors originating from the system environment in which one interacts. With regards to smart EV charging, the social conversion factors are more related to the state of mind of other individuals for instance; the willingness of EV owners to buy or sell electricity on the platform. The willingness of other EV owners determines the added-value for other EV owners to use the platform. They shape the possibility for EV owners to transact on the platform.

The willingness to buy or to sell is directly influenced by the incentive of an EV owner to charge or not. When the charge of an EV gets below the acceptable charge threshold, the EV owner will charge its EV. This EV owner will actively search to buy electricity when participating in the smart EV charging environment. Alternatively, when the EV charge is above the accepted charging threshold, the EV owner can strategically sell its electricity. The willingness of all participants in the system combined determine supply and demand and shape the system.

In addition, the personal conversion factors of other EV owners as presented in section 4.2, also serve as social conversion factors. When focusing on an individual EV owner, the charging patterns of others, ultimately determine the usefulness of the system. Within the CA, this phenomenon originates from the social context. The personal conversion factors of other users directly influence both the personal conversion factors and the preference mechanism of a person.

4.4. Social and technological context

According to the capability approach, a social context overarches the individual capabilities, choices, and conversion factors of EV owners. This social context is a blend of various norms (social and legal), the behaviour and attributes of other people, and environmental factors (Robeyns, 2005). The social context interacts with the individual's preference formation mechanism. In other words, the behavioural intention of an individual whether to perform an action depends on both personal and social conversion factors as well as social contextual influences. This section elaborates on the identification of the social context.

The starting point for identifying the social context is the representation of the capability approach as presented by Robeyns (2005) shown in figure 13. It was earlier determined that a total of five capabilities are considered. Whether they are enabled, depends on the initial technology assembly. For an individual to use the platform and achieve its functioning, personal preference, social pressure, and other decision-making mechanisms are in play (Zheng & Walsham, 2008). The previous sections have already identified the personal conversion factors which determine whether the individual is enabled to use the capability set.

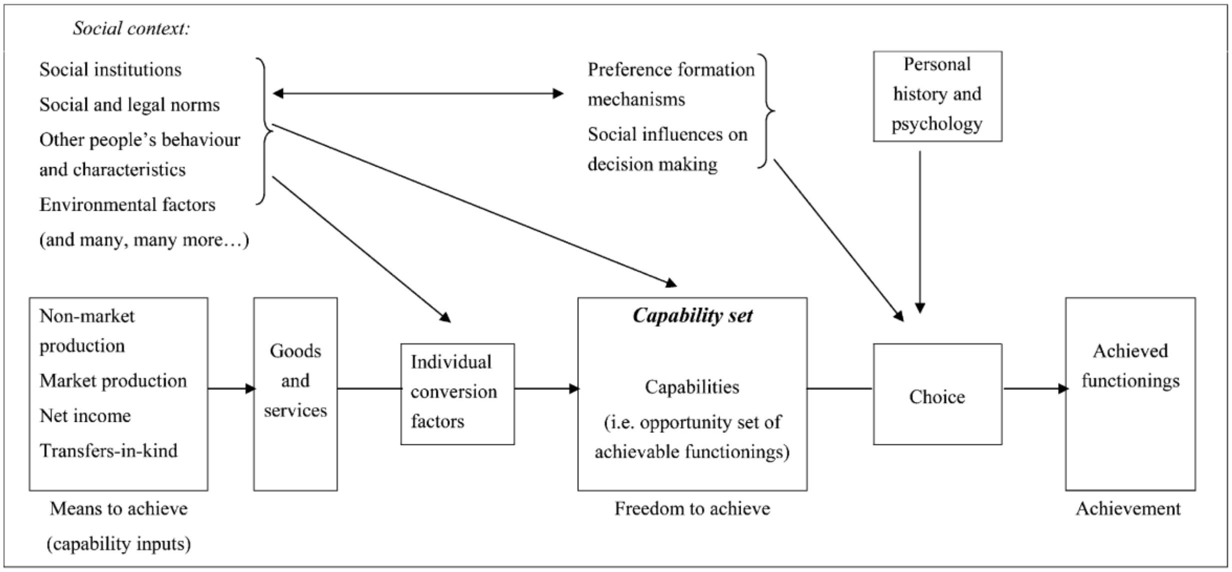


FIGURE 13 CAPABILITY APPROACH FRAMEWORK PROPOSED BY ROBEYNS (2005)

Conversion factors are dynamic; they constantly change depending on the technology, other user's behaviour, and individual actions. Robeyns (2005) identifies these changes as a direct effect from the social context on individual conversion factors as well as an indirect effect on the preference formation mechanisms of an EV owner. This preference mechanism ultimately determines the choice of an EV owner to make use of the platform or not. Sen (1993) has in part constructed the capability approach as a reply to the dynamics of decision making. A theory is needed to fill up the gap of preference formation both defining and explaining the dynamics of preference formation.

Cookson (2005) States that it could be well possible to adapt standard preference-based valuation methods in order to valuate capability sets. This implies that, next to the normative conscious and unconscious value judgement, other preference mechanisms are at play. Sen (1993) states that choices depend on expectations. These expectations depend on the limitations of the individual. Furthermore it is stressed that these preferences might have been shaped by societal processes (Robeyns, 2000). Thus, the theory in question should include a mechanism for expectation of added value as well as a societal component. In line with this assumption is the research model of the unified theory of acceptance and use of technology (UTAUT). UTAUT underlines that behaviour intention is determined by four key constructs:

- *Performance expectancy*
- *Effort expectancy*
- *Social influence*
- *Facilitating conditions*

The four constructs within UTAUT are used to identify the social and technological context (Venkatesh et al., 2012). Reflecting on these constructs in light of the capability approach immediately suggests that facilitating conditions resemble the conversion factors of individuals. Performance expectancy, effort expectancy, and social influence remain to affect the behavioural intention of an individual to select a capability which is most valued. This corresponds with the description of Venkatesh et al. (2012) regarding the separation of the four constructs. These constructs have been linked to the technology as well as the capability approach to create a conceptual overview of the social and technological context.

Moving away from the somewhat vague terminology, the concept of interaction is as follows: Users have their own personality (skill, intelligence, charging pattern, driving distance, and battery range). Their personality determines whether they are able to use the smart EV charging platform. This ability is determined by the complexity of the platform as well as how other users interact within the platform's environment. Furthermore, whether a user will actually use the system depends on the personal added-value this system has. This added-value is established by the expected effort and performance. All interactions in the system, were it with other users or with the platform, establish an overarching social environment which affects all users in the system. The effects are different for each agent depending on their personality.

4.4.1. Social influence

Social influence is the extent to which EV owners change their preference according to the actions and states of other individuals (Venkatesh et al., 2012). In terms of the capability approach Robeyns (2005) describes this as behavioural and personal changes in the social context. Social influence is something we don't always personally experience and the effects differ from one EV owner to another.

The value of a technology to a user increases with the number of users in the network. This phenomenon is referred to as network effects. It is assumed that direct network effects are of importance with respect to the usability of a smart EV charging platform. The usefulness for a potential user increases with the number of platform users due to the increased potential of user-matching. User-matching resembles the possibility that a new system user finds a peer with opposite charging behaviour. According to Hall and Khan (2003), network effects persist over time but have a decreasing effect.

This first phase after technology introduction relies on early users to share expectations and experience about the future value of the system. These early users may be willing to support a new platform and accelerate the network of users. Uncertainty about the platform's potential is high in the first phase of implementation. According to UTAUT social effects are strongest on lower skilled people, implying that the effect of social influences decreases when skill increases. Venkatesh et al. (2012) state that the reason for the declined effect of social influence can also be explained by the decrease of the technology's novelty. The extent of these effects remain uncertain, further implying the need for an exploratory approach.

4.4.2. performance expectancy

Performance expectancy is the extent to which users believe that using the platform has sufficient gains for them. To this regard preference is placed in a capability which is most valued by the user. This highly depends on the technological characteristics of the technology. Furthermore, blockchain is in essence a multi-user system, meaning its usefulness increases with the number of participants. At the initial introduction of the platform, the utility delivered is limited by the small scale and network effects work against more users switching to the platform (Catalini & Gans, 2016). Furthermore, personal skill and intelligence increase the expectancy of the system to be useful.

As mentioned earlier, finding a peer, which has opposite charging behaviour, is essential to ensure that demand and supply match. When a user is opting to participate on the platform, the platform's effectiveness will depend on the charging patterns of the new participant as well as the charging patterns of the established group of participants.

4.4.3. Effort expectancy

Effort expectancy is the expected degree of difficulty a new user associates with system usage. As with performance expectancy, individual characteristics like skill and intelligence determine the expected effort. Usefulness of a technology increases, when the technology becomes easier to use (Davis, 1989). The technological layout determines the flexibility the system enables. Effort expectancy therefore depends on personality, the required skill to use the platform, and the flexibility of the platform.

An important notion is that it doesn't revolve around *perceived* ease of use, which is a determinant of user acceptance. When the skills of an individual surpass the complexity of the technological system, this system has a degree of usability for the user. This degree of usability is supplemented by the performance of the system. As earlier mentioned, this performance is directly linked to the number of system users. Therefore it is not *perceived* ease of use, but *actual* ease of use.

4.5. Conclusions

Research sub-question 2:

"Which individual personality factors contribute most to the differences between individual EV owners? "

A total of five personal conversion factors was identified: Skill, intelligence, charging patterns, daily driving distance, and battery range. These personal conversion factors determine whether an individual is able to use the system. They also influence the larger social context, which shapes a social influence which affects all other users in the system. The personal conversion factors change according to changes in the technology, changes in the social context, and whether the EV owner uses the system.

Four constructs originating from UTAUT are identified, which help conceptualising the social and technological context. Social influence, effort expectancy, performance expectancy, and facilitating conditions are chosen as core concepts in defining the model environment. These constructs form the basis for quantification of the conceptual model.

Combining all conceptual structures, data, and information flows, the conceptual smart charging environment as presented in figure 14 was constructed. This conceptual model serves as the backbone for model building. Within the next chapter the different aspects within the conceptual model are quantified to serve as input for the agent-based model.

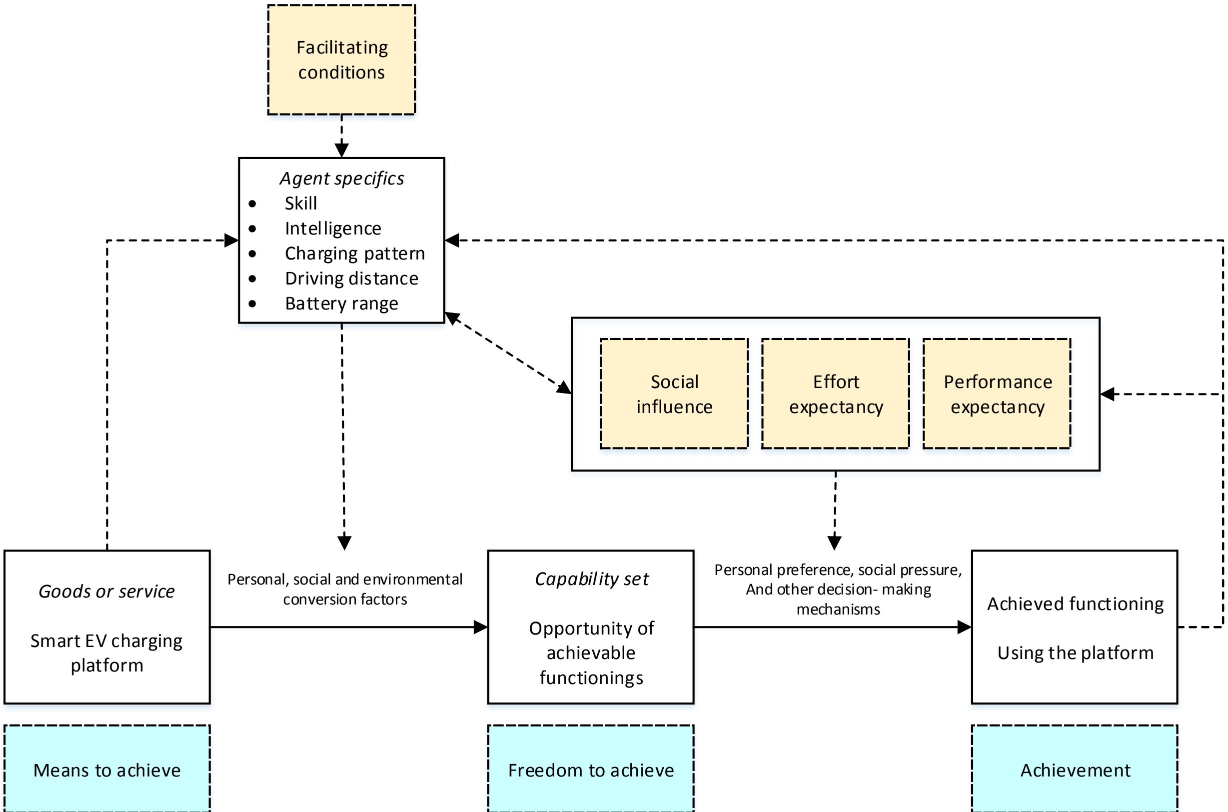


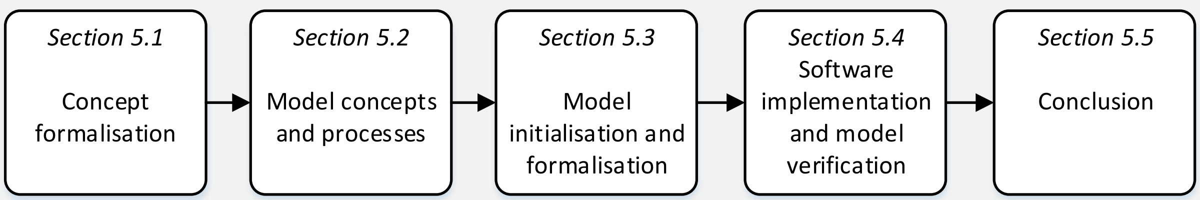
FIGURE 14 CONCEPTUALISED SMART CHARGING ENVIRONMENT

5. Model development

Structure

This chapter presents the conceptualised agent-based model. This chapter describes the steps of converging the insights from previous chapters towards a conceptual model. The conceptual model serves as the input for model formalisation. Model conceptualisation includes determining the level of the different user conversion factors as well as the technology design elements. Furthermore, the effects of the different technology design assemblies on the system-usability for the different agents in the system will be determined.

Section 5.1 describes the formalisation of the included concepts. Section 5.2 details the concept and processes with respect to their internal functioning within the model. The different concepts and processes are quantified by several equations and flow diagrams. Section 5.3 describes the model initialisation and formalisation. Section 5.4 concerns a brief description of the model implementation and the model verification process. The chapter is concluded in section 5.5.



5.1. Concept formalisation

This section elaborates on the different model concepts, taking the conceptual framework of CA interaction as presented by Robeyns (2005) as a starting point. In section 5.1.1 the different model input values are discussed and their quantification made explicit. Section 5.1.2 details the desired outcomes of the model.

5.1.1. Model input

Four main categories of model input are considered: Technological layout, taxonomy of technology, number of EV owners, and distribution of states (conversion factors). This section will quantify the acquired data from previous chapters.

Technological layout

Chapter three identified four core design decisions. Xu et al. (2017) identified different levels within these four design decisions. These specific levels were chosen as model input and the model user is able to differentiate between them. Table 7 details the different design options. The design space makes for 81 different technological design options when taking into account all possible combinations.

Design option	*Level of decentralisation*	*Data storage method*	*Blockchain configuration*	*Consensus protocol*
Alternative 1	Decentralised	On-chain smart contracts	Public	Proof-of-work
Alternative 2	Semi-decentralised	On-chain log events	Consortium	Proof-of-stake
Alternative 3	centralised	Off-chain data storage	private	Byzantine fault tolerance

TABLE 7 TECHNOLOGY DESIGN OPTIONS

Quantifying technological design decisions

Each technological layout has different implications for the four scoring criteria as presented in the taxonomy of Xu et al. (2017): Fundamental properties, performance, flexibility, and required skill. Fundamental properties represents the ability of the system to safeguard trust, data privacy, and scalability (Xu et al., 2017). Flexibility concerns the system's ability to adapt to changing circumstances. For instance decentralised public blockchains fundamentally cannot be changed after implementation and are therefore less flexible. Required skill represents the amount of skill an EV owner needs to have in order to properly use the system.

With respect to the taxonomy, scores are assigned to an alternative through a quantity of *points*. For the agent-based model, these points are transposed to fractions by assigning a score of 0.1 for each *point* this alternative scores according to the taxonomy. Using this point system, the best alternative gets a score of 0.3 and the worst alternative a score of 0.1. When all scores are calculated for each of the three design options, they are combined to calculate the score for the system as a whole. When this score is above 1, it is considered a high score. Take note, that this score does not represent a realistic scoring criteria. It is merely used to compare alternatives regarding the four scoring criteria. Table 8 includes the scores for each alternative regarding the four scoring criteria.

Design option	Design alternatives	Performance	Flexibility	Required skill	Fundamental properties
Level of decentralisation	Decentralised	0.1	0.1	0.2	0.3
	Semi-decentralised	0.2	0.2	0.15	0.2
	centralised	0.3	0.3	0.1	0.1
Data storage method	smart contracts	0.2	0.1	0.2	0.3
	log events	0.1	0.2	0.15	0.3
	data storage	0.3	0.3	0.1	0.1
configuration	Public	0.1	0.1	0.1	0.1
	Consortium	0.2	0.2	0.15	0.2
	private	0.3	0.3	0.2	0.3
Consensus protocol	Proof-of-work	0.1	0.1	0.1	0.3
	Proof-of-stake	0.2	0.3	0.15	0.2
	Byzantine fault tolerance	0.3	0.2	0.2	0.1

TABLE 8 TECHNOLOGY SPECIFIC VALUES FOR MODEL IMPLEMENTATION BASED ON XU ET AL. (2017)

Number of EV owners and time configuration

The number of EV owners in the system was chosen in such a way that it allows for system behaviour to emerge while retaining a manageable model run time. Within the system, a model tick represents 24 hours. A model run of 200 ticks is chosen. After 200 ticks, most system behaviour converges to an optimal point. A total of 200 EV owners are modelled.

Distribution of states

Several properties of the model require distributions to assign values to agents. For the agent-based model, five of such distributions were implemented, namely: charging patterns, driving distance, battery range, skill, and intelligence.

The *Charging patterns* of EV owners can be categorised between low- and high- intensity (Franke, Bühler, Cocron, Neumann, & Krems, 2012). The categories should follow a normal distribution. Franke et al. (2012) could not define a normal distribution accounting for all charging patterns. However, a normal distribution seemed most fit. Therefore, for modeling purposes a normal distribution with a mean of 0.5 is implemented. The normal distribution is complemented by a manually assigning a normally distributed spread of 0.1 The corresponding normal distribution is presented in figure 15. Lower levels of charging pattern indicate that an EV owner will start charging when his battery charge is at low levels. Higher levels of charging pattern indicate that an EV owner will more regularly start charging its EV. Take note that the word *pattern* in *charging pattern* doesn't indicate that a driver changes its charging behaviour over time. It represents the level at which an EV owner will start charging its EV.

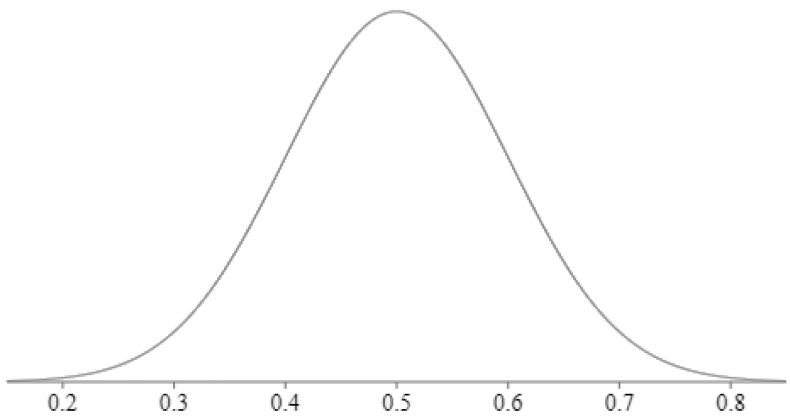


FIGURE 15 CHARGING PATTERN DISTRIBUTION BASED ON A NORMAL DISTRIBUTION

Driving distance is distributed from zero kilometers a day (people who leave their car at home for the day) up to 200 kilometers a day. Wu et al. (2010) concluded that the driving distance spread decreased exponentially from zero to approximately 200. Concerning the data used in the research, the driving distance is distributed according to figure 16. The same distribution is used within the agent-based model.

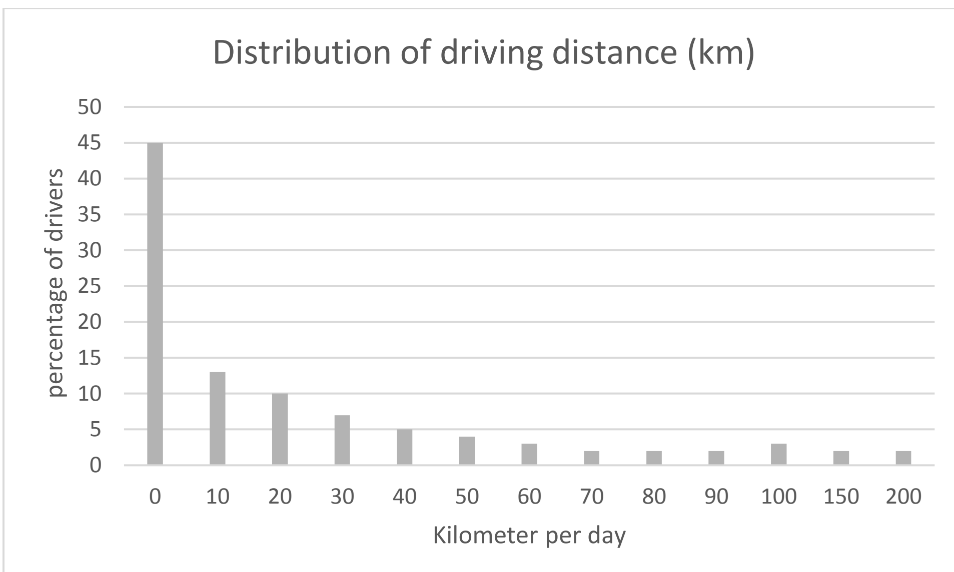


FIGURE 16 DRIVING DISTANCE DISTRIBUTION OF EV OWNERS BASED ON THE RESEARCH OF WU ET AL. (2010)

Battery range is different for each EV owner within the model. It is assumed that the distribution between EV owners is a normal distribution between 150 and 500 kilometers of battery range. The battery range is distributed according to figure 17. *Skill* and *intelligence are* uniformly distributed between 0 and 1, such that 0 represents low skill and 1 represents high skill.

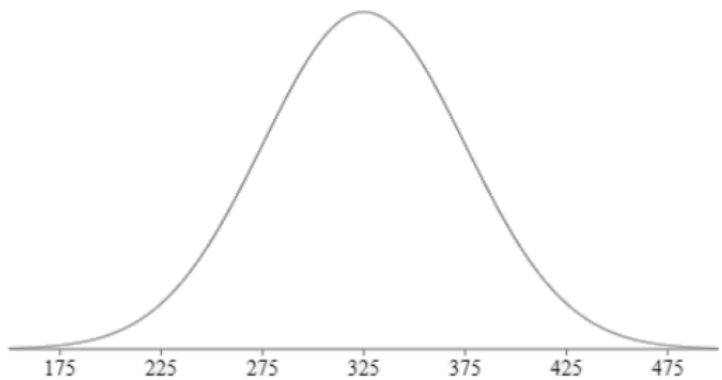


FIGURE 17 DISTRIBUTION OF BATTERY RANGE OF EV OWNERS

5.1.2. Model outcomes

In line with the main research objectives, the model should produce outcomes which can be used to gain insights in factors contributing to *Performance*, the *number of users* on the short- and long-term, and *ethical implications*.

Performance is assumed to be related to the number of system users, the amount of electricity that is bought and sold through the platform, and the number of processed transactions. Small fees could be integrated within smart contracts based on subscriptions of users or a portion of the electricity sold. This would potentially yield monetary benefits for the system operator.

The number of users at a given moment highly depends on personal preferences, the state of the system, and the social influences experienced by a potential user. Due to continuous changes along these parameters, users can opt to use the system or stop using the system. This results in model data which shows the number of users. The way this data behaves yields insights for short- and long-term system usage.

Ethical implications are expected to increase when more users enter the system, more data is stored, and more transactions take place. Each technological design has a certain ability to cope with these ethical implications. The model should present which technological designs are more robust in terms of mitigating these ethical concerns and, in other terms, fulfil the values of EV owners.

5.2. Model concepts and processes

Within this section, the different interactions and concepts are detailed and their formalisation within flowcharts is elaborated on. Flowcharts are used as they provide a better means of communicating the system logic. Furthermore, they aided with structuring the code implementation within the model building phase. Six main concepts are implemented regarding the use of the smart charging platform. Furthermore five concepts describe the scoring mechanisms with respect to the ethical values.

5.2.1. Skill increase

One of the main concepts within the model is skill increase of EV owners. This concept resides on the concept of networking effects. The skill of EV owners represents the ability to comprehend with the difficulties the system layout poses. In general terms, the higher the skill, the more easy the EV owner can use the system and the more added-value the system has. To determine whether and by how much skill should increase, it is important to know whether the EV owner already uses the system or not.

Research showed that hands on experience increases the attainment of skill. Furthermore, when the system is used, the social influence is expected to be higher due to the increased interaction between system users. These network effects can best be understood as the representation of the social standard within the community. Reflecting on these concepts, when an EV owner uses the system, skill increase is based on the social influence, the current skill of the EV owner, intelligence, and network effects.

Network effects tend to decrease when the skill of an individual increases. Therefore, when the skill of a user is high, this user will yield less benefits from network effects. For users which don't use the system, network effects are not at play since these users don't interact within the systems environment. Therefore these users will yield minimal social influence. Their skill will increase much slower as compared to system users. The model logic is presented in figure 18. Considering the aforementioned, skill increase is calculated using the following factors:

- ω : Skill of the agent at previous instance
- φ : Intelligence of the agent
- θ : Social influence on this agent
- τ : Minimum skill increase factor
- L : Skill de-linearisation factor

When the agent is a system user, these factors are subject to:

$$Skill = \omega + \Big(\big(1 - (\omega * L)\big) * \varphi * \theta\Big)$$

EQUATION 1 SKILL INCREASE FOR SYSTEM USERS

When the agent is not a system user, these factors are subject to:

$$Skill = \omega + (\tau * \varphi * \theta)$$

EQUATION 2 SKILL INCREASE FOR NON SYSTEM USERS

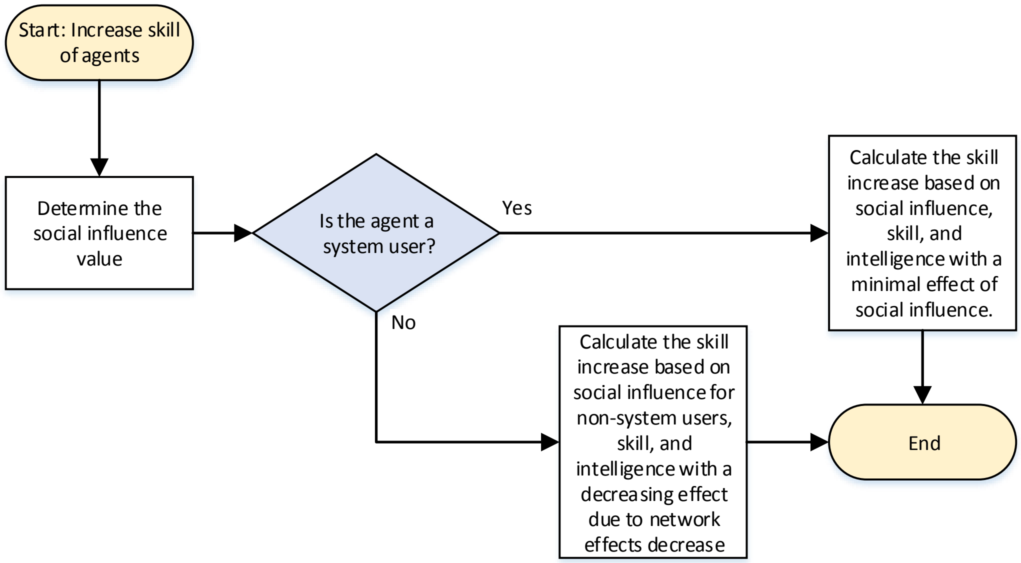


FIGURE 18 FLOWCHART FOR SKILL INCREASE

5.2.2. Updating the social context

Within the capability approach, capabilities of people are expanded by a social context. Within this thesis a link between this social context and quantifiable effects was made. Refraining to agent-based modeling, this social context is perceived as the arrangement of effects caused by actions and states of other users in the system. Its function in the agent-based model is twofold. Primarily it represents the degree of social networking effects an agent experiences based on the number of users in the system and the combined skill of these users. Basically, when the system is used by highly skilled individuals, a new user yields higher social benefits from the experienced community than when the system is used by less skilled individuals. However, the degree to which this new user is affected depends on which level of skill it has already acquired. Secondly, The charging patterns and driving distances of other users in the system determine the added-value of the system for new system users. Users with similar charging patterns yield less added-value as their demand and supply schemes will align and results in the disability to sell electricity to one another. Therefore, new users with different charging schemes have a higher chance to sell and buy electricity. Figure 19 shows the process of determining the social context value for an EV owner

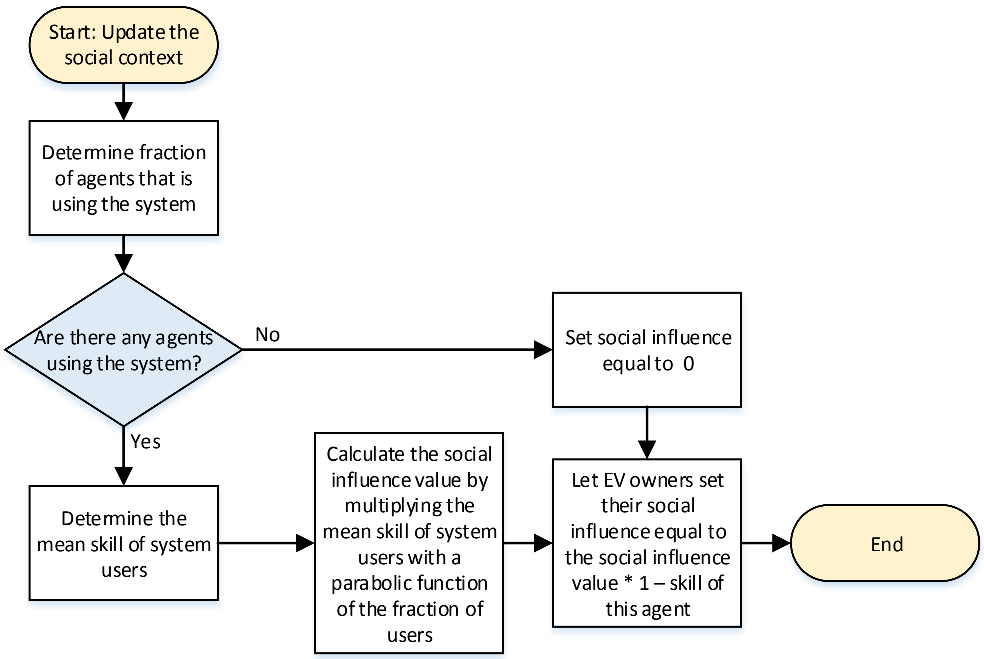


FIGURE 19 FLOWCHART FOR UPDATING THE SOCIAL CONTEXT

5.2.3. Determine system usage

The capability approach defines clear steps for an EV owner from non-user towards user. Before a user is able to decide on whether it wants to use a system or not, this user is required to have a minimum amount of skill, which is determined by the complexity of the system. When the potential user surpasses the threshold for system entry, this user becomes enabled to use the system. The next step in the process of system entry is to define whether the system has enough added-value for this potential user. This added value is determined by two factors, namely, effort expectancy and performance expectancy. These factors are determined by even more factors.

Performance expectancy is determined by the system properties, the system environment, and specifics of the potential user. When there are no system users, it is assumed that a potential user will not determine the expected performance based on the system environment, but solely on its own state and the system itself. The other scenario is more complex. When the system has users, the added-value of the system is, logically, higher than without users. The extent is determined on what charging pattern the system users have, and how these charging patterns differ from the potential system users. Smart charging requires different users with regards to charging patterns. Different charging patterns increase the possibility of users to sell and buy electricity as the users charge and discharge at different times and with different quantities. It was already explained that users with a lower charging pattern (people who charge at a certain battery level instead of every evening) are more useful in a smart charging environment. Consequently, when the users of the system have an overall high charging pattern, and a potential user has a low charging pattern, the performance of the system for this particular EV owner is high. A moderator-value is included to decrease the performance when there are no system users. The numerical value is uncertain and requires further exploration.

In calculating the performance expectancy of the system, the following factors are assumed to have an effect on the performance:

- ω : Skill of the potential user
- φ : Intelligence of the potential user
- σ : System-performance of the platform
- $\alpha(S)$: The number of users that use the system
- θ : The supply of electricity
- ϑ : The demand for electricity
- α : The number of EV owners in the model environment
- β : The mean of all charging patterns of system users
- τ : The charging pattern of the potential user
- γ : The fraction of higher charging patterns in the system
- μ: Moderator-value when no other system users

In calculating the performance expectancy for a particular agent, assuming no other system users, the above stated factors are subject to:

$$Performance\_exp = \omega * \varphi * \sigma * \mu$$

EQUATION 3 PERFORMANCE EXPECTANCY WITHOUT SYSTEM USERS

In calculating the performance expectancy for a particular agent, assuming other system users, the above stated factors are subject to:

$$Performance_{exp} = \omega * \frac{\alpha(S) * \frac{\vartheta}{\theta}}{a} * \varphi * \sigma + (\beta - \tau) - \left(\frac{\gamma}{\frac{\alpha}{a(S)}} \right)$$

EQUATION 4 PERFORMANCE EXPECTANCY WITH SYSTEM USERS

Effort expectancy is determined by the required skill of the system layout compared to the skill of the potential users. Furthermore, the smart charging environment has a degree of flexibility. This flexibility is perceived as the extent to which the system can adapt to different users. The higher the flexibility, the lower the expected effort. The full process of system usage is presented in figure 20. Three factors are assumed to determine the effort expectancy for a potential user of the system, namely:

- β : required skill for using the platform
- ω : skill of the agent
- δ : system flexibility of the technology layout

Depending on whether the system has any flexibility the factors are subject to the following equations:

$$Effort_{expectancy} = (\beta * (1 - \delta)) - \omega$$

EQUATION 5 EFFORT EXPECTANCY WITH SYSTEM FLEXIBILITY

$$Effort_{expectancy} = \beta - \omega$$

EQUATION 6 EFFORT EXPECTANCY WITHOUT SYSTEM FLEXIBILITY

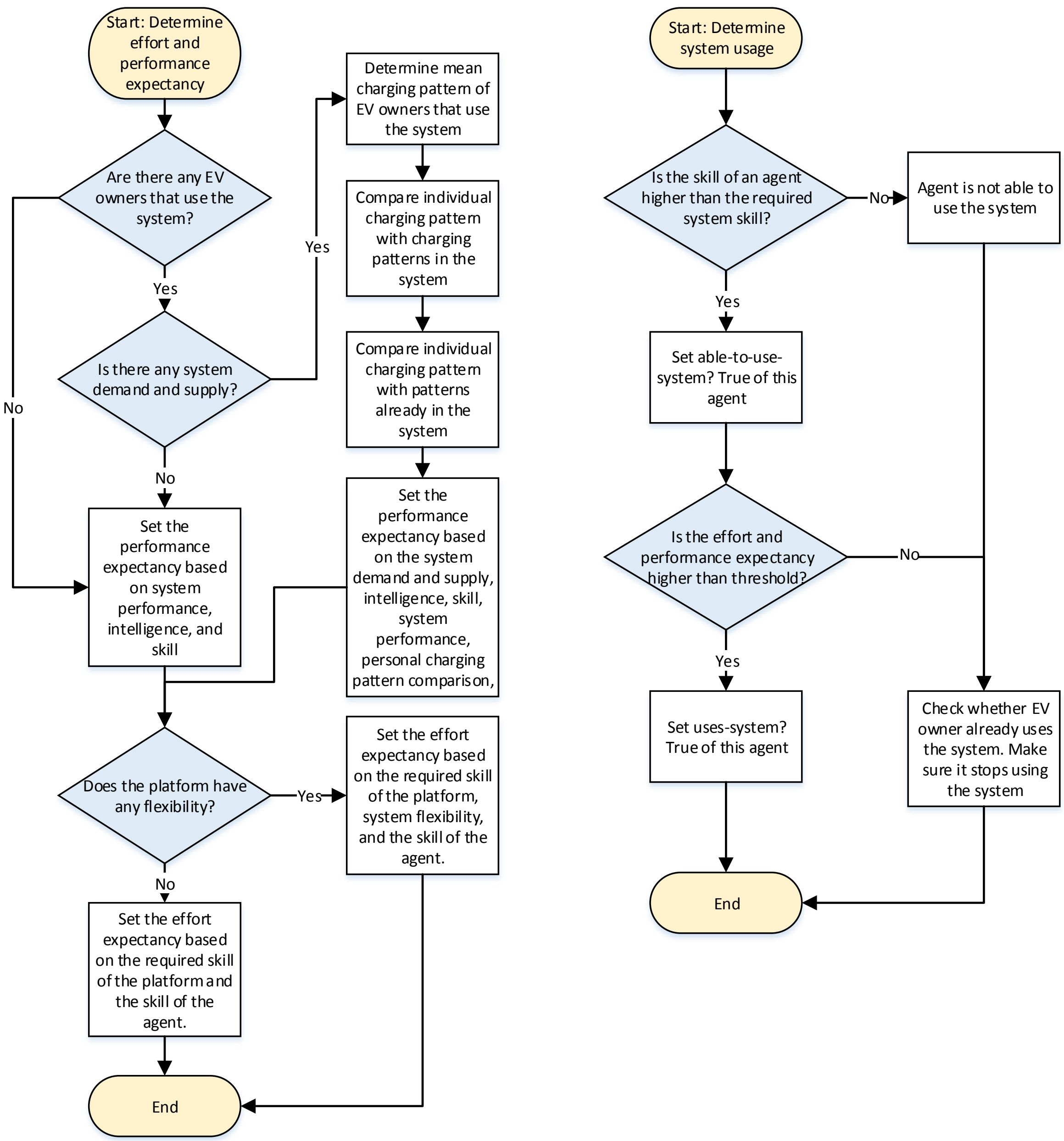


FIGURE 20 FLOWCHART FOR DETERMINING SYSTEM USAGE

5.2.4. Update EV charge

A simple yet crucial concept within the model is the decrease of battery charge due to the daily driving distance of EV owners. This process is presented in figure 21. Each day the battery range decreases depending on the driving distance, and the total battery range. After the agent has driven its daily distance, it will check whether its EV charge is still above its charging pattern threshold. When this is the case, this agent will not aim to charge its electric vehicle but is willing to sell its surplus (difference between charge and charging pattern) to other system users. When this is not the case (i.e. the EV charge is 60% while the agent wants to charge at 80% charge), this agent is aiming to buy electricity.

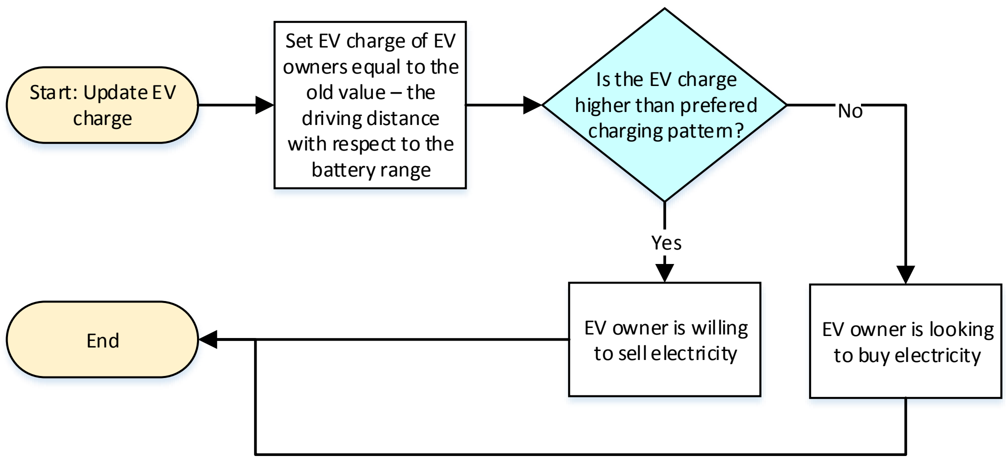


FIGURE 21 FLOWCHART FOR UPDATING EV CHARGE

5.2.5. Update demand and supply

It was earlier mentioned that the performance and therefore the added-value of a system depends on how much electricity is demanded and supplied. A surplus of either results in the system being less efficient. An optimal scenario is where both demand and supply are equal and charging patterns are evenly distributed among the system users. Demand is established each tick by summing the individual demand of agents that aim to buy electricity. Total system supply is calculated in a similar manner. The flowchart for the model logic used for determining electricity demand and supply is visualised in figure 22.

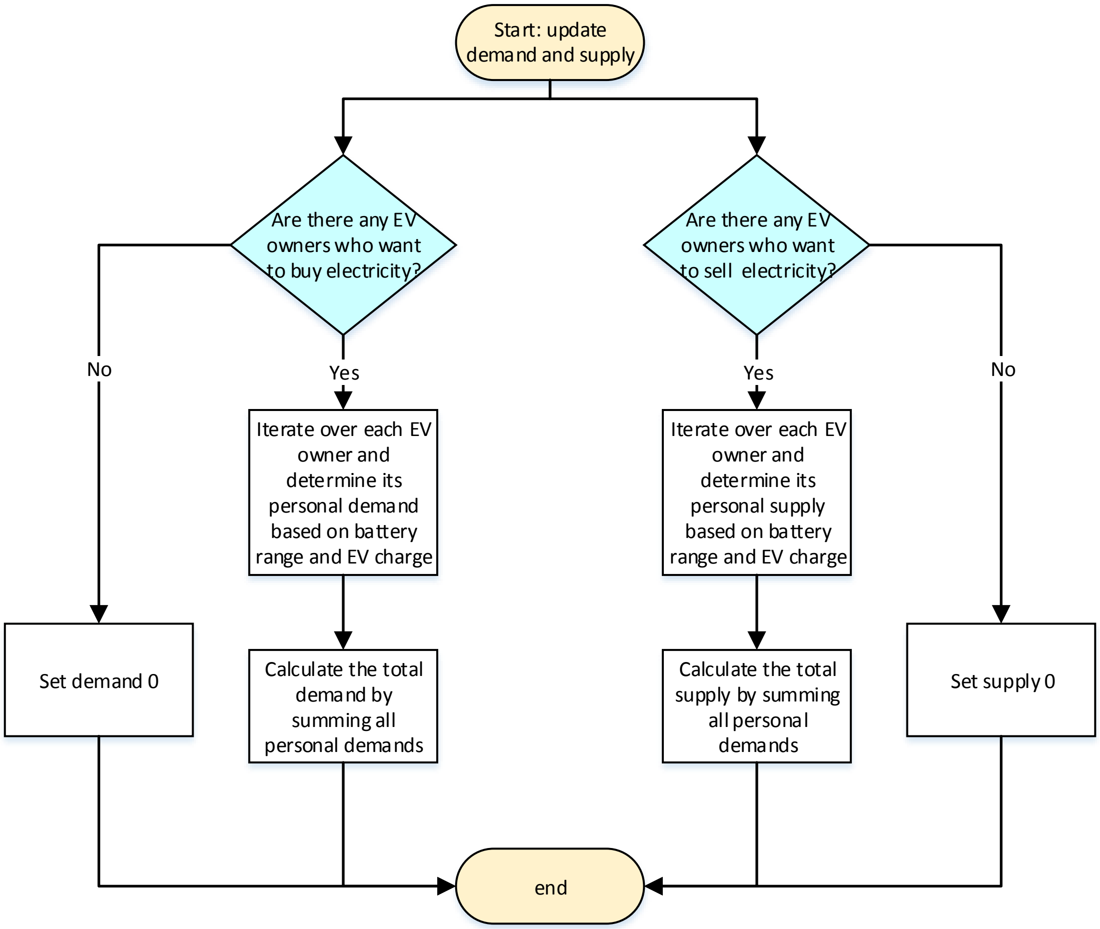


FIGURE 22 FLOWCHART FOR UPDATE DEMAND AND SUPPLY

5.2.6. Trade electricity

The fundamental property of a smart charging system is to enable users to trade electricity. This process is executed after it is determined whether an EV owner wants to buy or sell electricity. When a user aims to charge its electric vehicle, it will communicate this to the platform. Within the mix and match environment, the platform is looking for EV owners which can supply the total sum of electricity at once. If so, the system will automatically match both peers, discharge the EV of the selling party, and charge the EV of the buying party.

When a one on one arrangement is not possible, the system will search for multiple EV owners which want to sell electricity. The system will then sort these selling parties on quantity of supplied electricity. The system will match the buying party with as many sellers that are needed to fully charge the buying parties' EV. Whenever the supply of the selling parties cannot fulfil the demand, the buying party will buy the supplement of electricity from the grid. The electricity trade process is presented in figure 23.

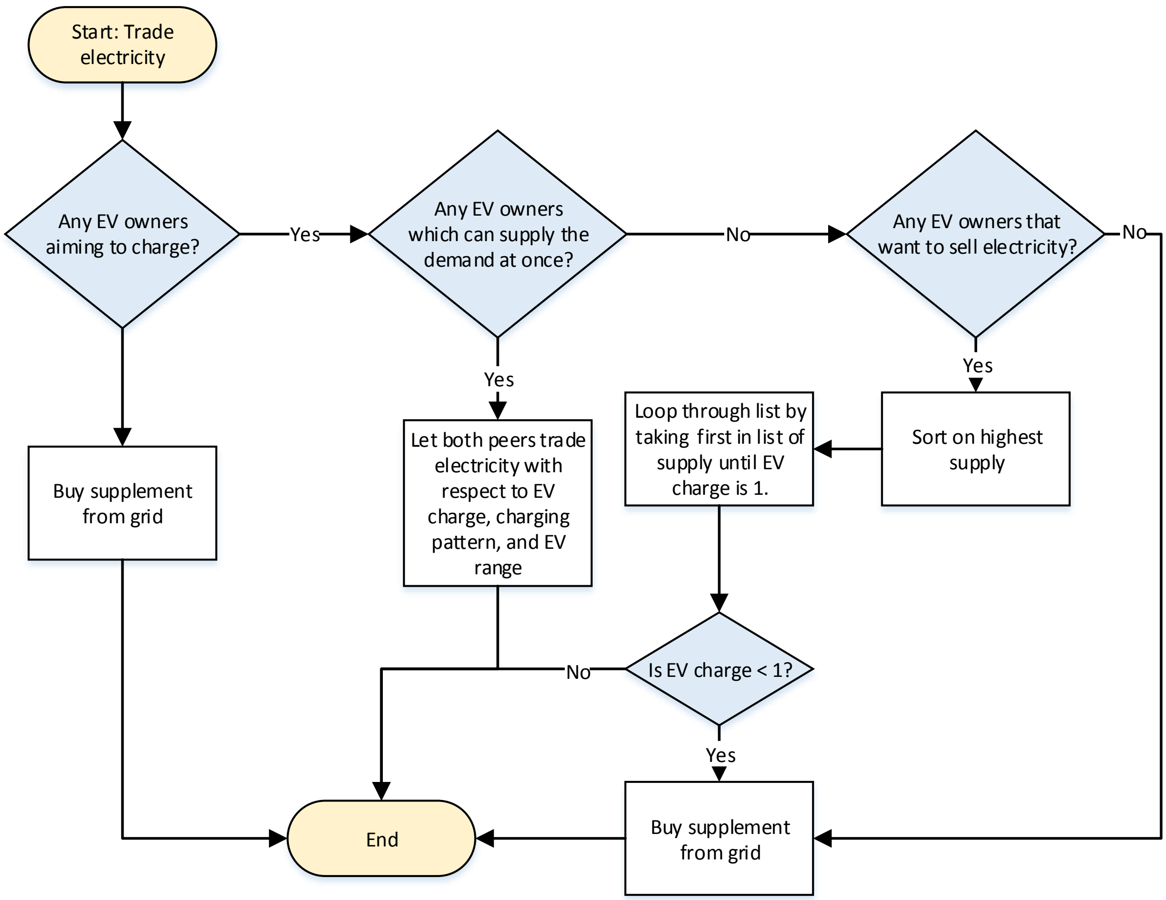


FIGURE 23 FLOWCHART FOR TRADE ELECTRICITY

5.2.7. Privacy score

Smart contracts for enabling transactions are trustless. They do not require trusted intermediaries to mediate the transaction. However they lack transactional privacy (Kosba et al., 2016). All information associated with a smart contract is transferred across the entire network and is publicly visible. Therefore, it is stressed that privacy is a significant obstacle towards the full integration of decentralised smart contracts. Figure 24 details the process of determining the privacy score when using a smart charging platform. The value of privacy fulfilment is presumably based on four factors:

- $\alpha(S)$: All users which use the system
- α : All users in the model environment
- β : The fundamental properties of the system based on technology layout
- I : Initial score based on best alternative

Subject to:

$$privacy_{score} = I - \sum \frac{\alpha(S)}{\alpha} * \beta$$

EQUATION 7 PRIVACY SCORE

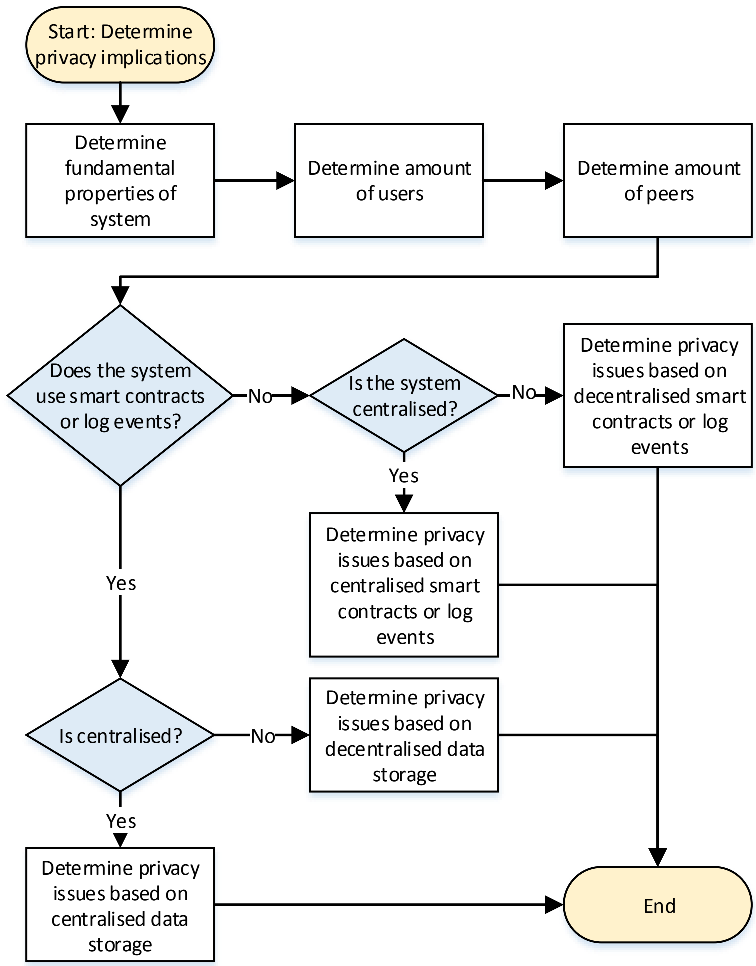


FIGURE 24 FLOWCHART FOR PRIVACY SCORE

5.2.8. Security score

Within the blockchain environment, data is protected by the consensus algorithm, which validates the transactions and identity of participants. These algorithms are run by nodes (participants) within the system. Consequently, they need users to work. The more participants the more effective the consensus protocol runs. For this research, two types of data storage were chosen, *on-chain* and *off-chain* data storage. On-chain data storage is more secure since data is protected on the blockchain which no third party can freely access. Off-chain storage implies external storage in either a cloud or an external storage facility. The storage facility is run by either the smart charging system designer or an external party. When the platform is centralised, the information is validated through *attestation* by a trusted authority, namely the operator of the smart charging platform. This creates a single point of entry which is prone to hacks and therefore less secure. This line of logic is presented in figure 25. The best scenario for data security would be to store the data on-chain with an effective consensus algorithm with a large number of users in a decentralised fashion. As with privacy, the security score is based on several factors:

- γ: The effectiveness of the consensus algorithm
- β: The fundamental properties of the system based on technology layout
- δ: Supplement based on design effectiveness

Subject to:

$$Security\_score = \gamma * \beta + \delta$$

EQUATION 8 SECURITY SCORE

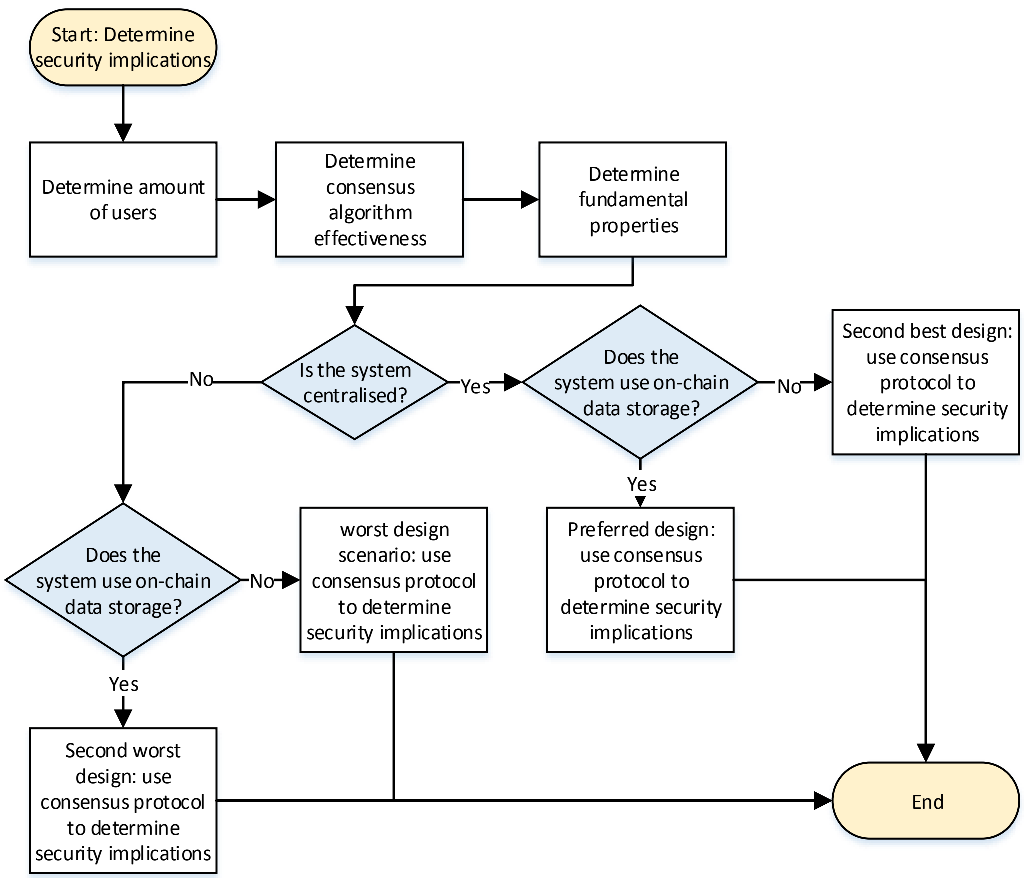


FIGURE 25 FLOWCHART FOR SECURITY SCORE

5.2.9. Trust score

A fully decentralised public blockchain network is in essence a trustless environment. Any deviation from this optimal design has implications for trust. Moving away from the decentralised layout towards a centralised one has the most impact on the trustworthiness of the network. Trust is shifted towards a single point within the network.

The value of trust was linked to the extent the system enables trustful participation for system users. Regarding blockchain applications, it tells something about the effectiveness of the system to enable a trustless environment. It was found in data that the effectiveness of proof-of-work or proof-of-stake algorithms has non-linear behaviour. Therefore, decreasing the number of users has a larger effect on these protocols than for instance byzantine fault tolerance. Therefore these consensus protocols have different formulas for calculating their effectiveness to enable a trustless environment. Calculating the trust score is done in two consecutive steps. First it is determined how effective the technological layout is regarding the fundamental properties of the system. The most optimal design gets a supplement and the less optimal design gets no supplement. Thereafter the number of users with respect to the total number of users in the model environment is assumed to increase or decrease the trust score of the system. The corresponding flowchart is visualised in figure 26. The following factors influence the trust score:

- β: The fundamental properties of the system based on technology layout
- $\alpha(S)$: All users which use the system
- α: All users in the model environment
- θ: Fundamental properties based on the technological layout
- ε: Supplement for best design

Subject to:

$$\theta = \beta * \varepsilon$$

EQUATION 9 FUNDAMENTAL PROPERTIES

If linear subject to:

$$Trust\_score = \theta + \frac{\alpha(S)}{a}$$

EQUATION 10 TRUST SCORE LINEAR

If non-linear subject to:

$$Trust\_score = \theta + \left(\frac{\alpha(S)}{a}\right)^2$$

EQUATION 11 TRUST SCORE NON LINEAR

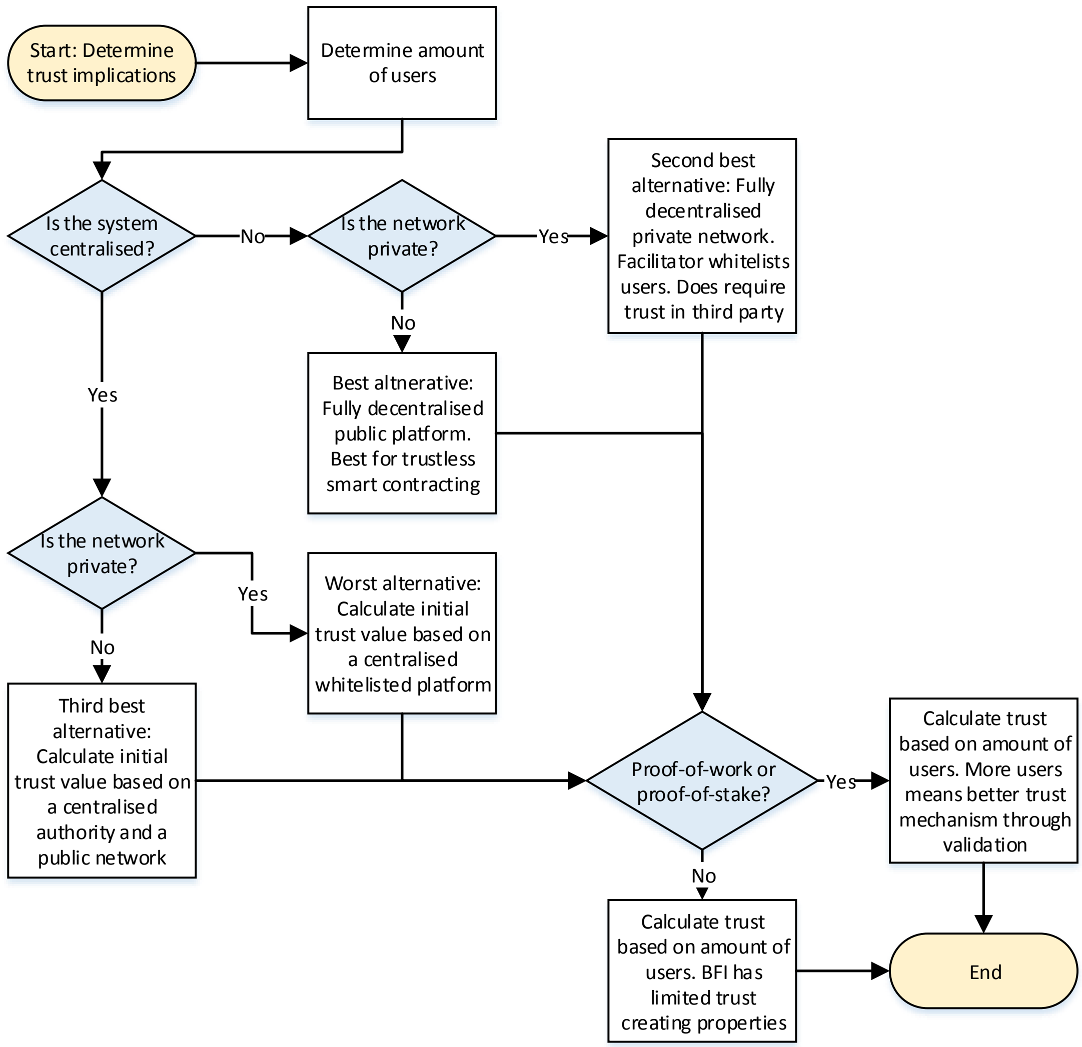


FIGURE 26 FLOWCHART FOR TRUST IMPLICATIONS

5.2.10. Confidentiality score

Regarding confidentiality, in a peer-to-peer trust environment, an individual user will determine what digital information is recorded on the blockchain and how that information will be used (Railkar, Mahamure, & Mahalle, 2012). Confidentiality relates to safeguarding that only the corresponding and authorised user is able to read information considered private. The more peers, the higher the chance that confidentiality issues arise. The more peers and transaction data, the more the system is prone to hacks. The process of determining the confidentiality score is presented in figure 27. As such, calculating the confidentiality score of the system is subject to the following factors:

- ρ : number of transactions this day (tick)
- σ : total number of platform trades
- τ : compensation factor for optimal designs
- ε : total number of days the system is implemented

These factors are subject to the following equation, determining the confidentiality score of the system:

$$Confidentiality_{score} = 1 - \frac{\frac{\rho * \varepsilon}{\sigma}}{\tau} * 0.5$$

EQUATION 12 CONFIDENTIALITY SCORE

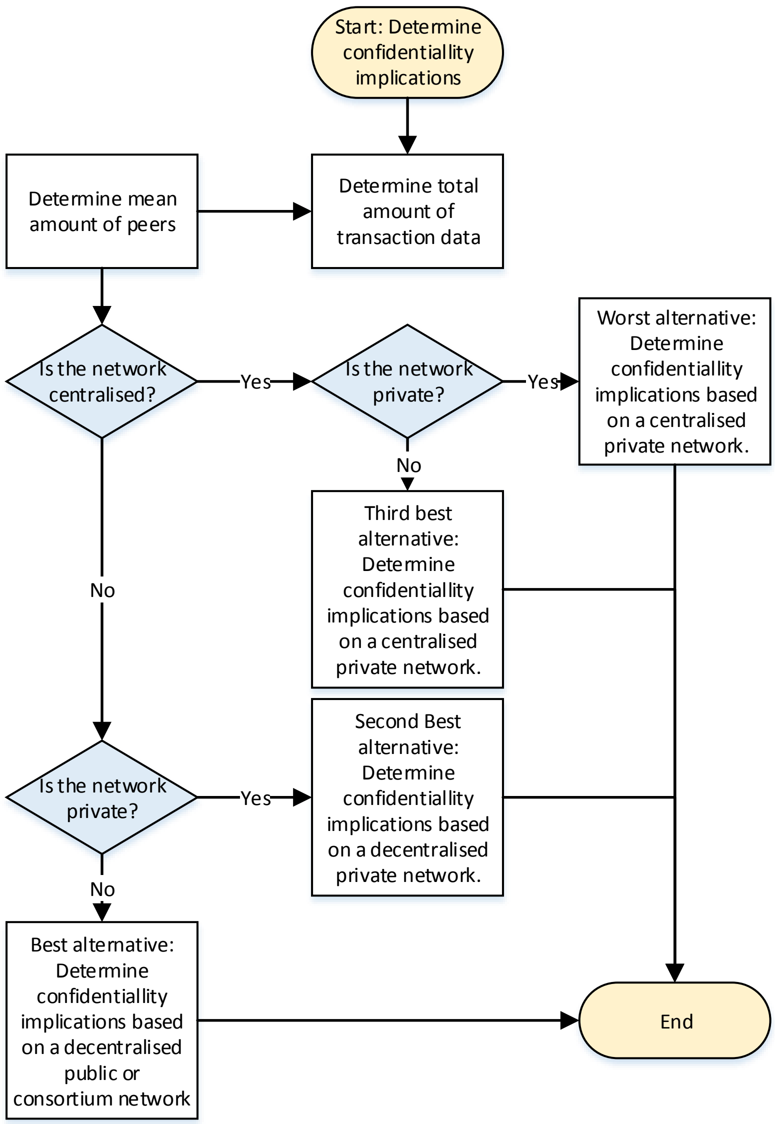


FIGURE 27 FLOWCHART FOR CONFIDENTIALITY IMPLICATIONS

5.2.11. Anonymity score

Identity anonymity can only be achieved when a significant number of people in the network vouch for the validity of the information in a user's profile. Within a "centralised" fashion the personal information is validated by a trusted authority. This does however require full trust in the third party. Anonymity is fundamentally less preserved when a single point of entry knows all personal information of participants in the system. Therefore, a fully decentralised system based on zero knowledge proof is most fit to protect the anonymity of the participants.

The system becomes more prone to hacks when more personal data is stored. Transactional data can be useful to interested parties. Therefore, it is assumed that the more transactions take place on the network, the more prone the network will become to hacks. This increases the risk of anonymity breach. The process of determining the anonymity score is visualised in figure 28. As such it is expected that anonymity is decided by the following five factors:

α: number of users in the model environment
β: The mean number of peers a platform user has
γ: The number of system users
δ: The fundamental properties of the system layout
ε: A compensation factor for the best possible design

These factors are subject to the following equation:

$$Anonymity\_score = 1 - \frac{\frac{\gamma}{\alpha}}{\left(\frac{2}{\beta}\right)} * \delta * \varepsilon$$

EQUATION 13 ANONYMITY SCORE

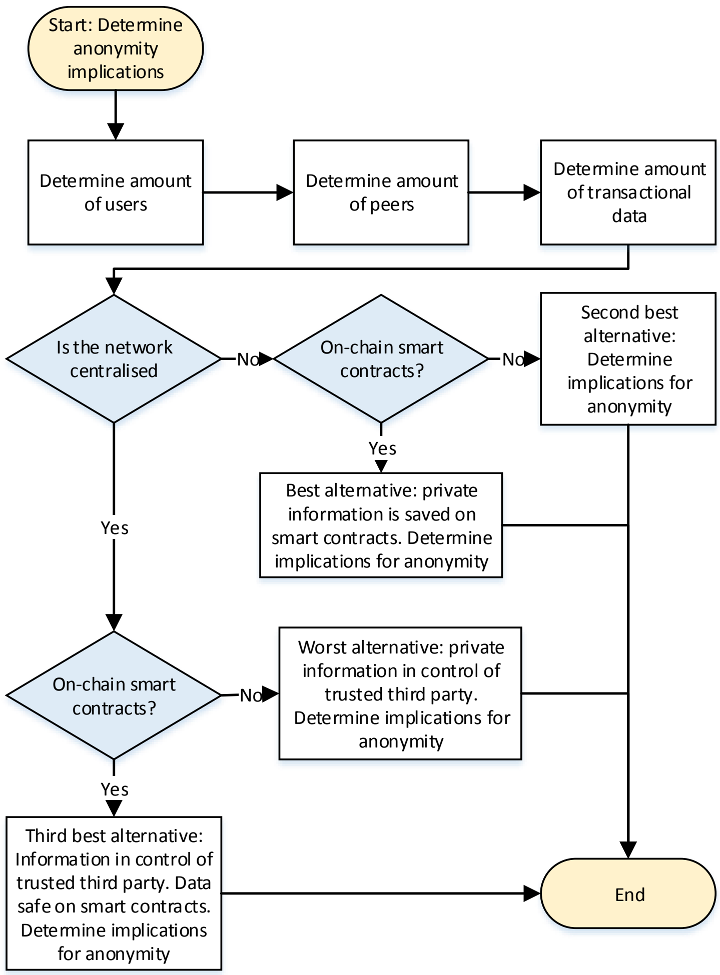


FIGURE 28 FLOWCHART FOR ANONYMITY IMPLICATIONS

5.2.12. System performance

The last concept to be implemented in the model is the performance of the system as a whole. Within this research performance is described in twofold. First, it is seen as the increase of users and their transactions. Note that the size of the transactions with respect to the number of kilometers sold or bought does not matter for this calculation. A sold kilometer relates to the amount of electricity needed to drive one kilometer. Since all calculations within the model are related to the number of kilometers an EV can drive, the KPI for the amount of traded electricity is also presented as number of traded kilometers. As such, the following factors are assumed to have an impact on the overall system performance:

- number of agents that use the system
- The number of transactions this day (tick)
- Total number of kilometers bought from the grid per day

5.2.13. Quantified conceptual model

The concepts and quantitative data are added to the conceptual smart EV charging model as presented in section 3.5. The result is the completed conceptual model as shown in figure 29.

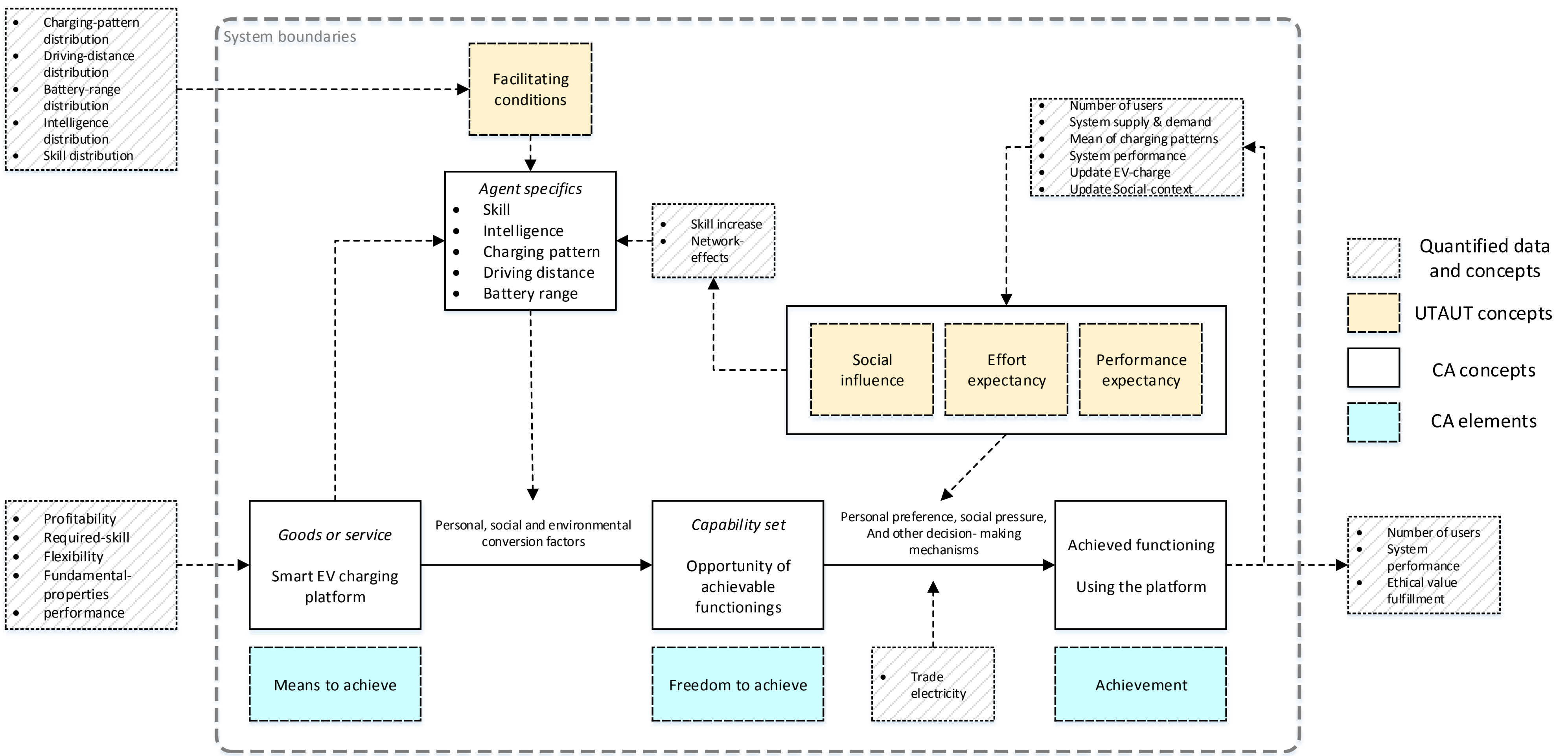


FIGURE 29 CONCEPTUAL SMART CHARGING MODEL

5.3. Model initialisation and formalisation

The next step within model development was to formalise the conceptual model towards agent-based modeling implementable language. Section 5.1 identified the different concepts and interactions present in the model. Before these concepts and interactions can be modelled, a list of states and actions was made. These states provide a detailed insight into which actions agents can perform and when they would eventually perform these. Appendix A elaborates on the different states of the EV owners, the charging platform, and the environment.

The model user can, to some extent, set up the model layout from the user interface. According to these setup settings, a model initialisation is executed which determines the starting point for a simulation run. Appendix B presents an overview of how the model initialisation works and which parameters can be altered by the system user.

In conclusion of the model conceptualisation and formalisation a model concept was constructed taking into account the data found in the previous chapters as well as a newly created conceptual framework based on the capability approach and constructs from UTAUT. The different concepts were worked out in flowcharts and framed within the smart charging environment. Figure 30 presents an overview of the various model inputs and model outputs as well as the interaction within the model environment itself.

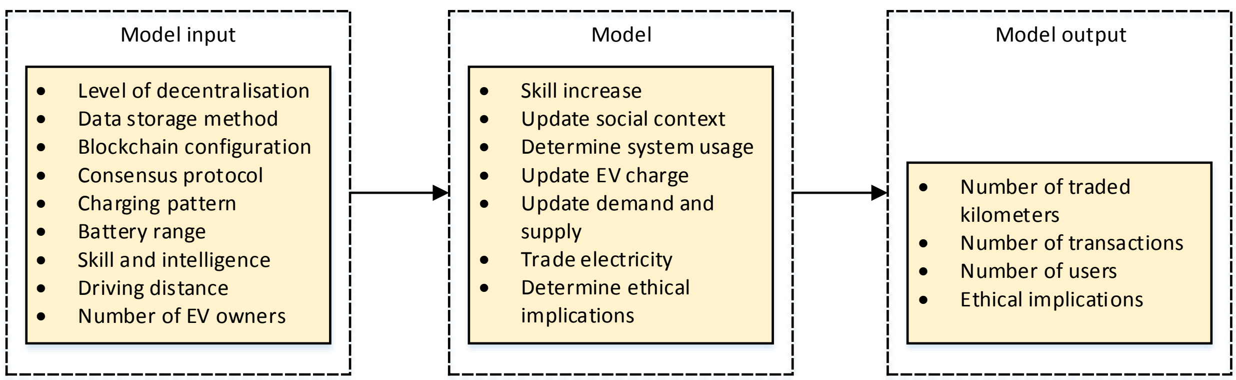


Figure 30 Model input-output diagram

5.4. Software implementation and model verification

In succession to the previous chapter, this chapter describes the steps undertaken to create the actual model. The formalised agents and flowcharts are translated to computable code which is implementable in a fitting modelling software package. For this agent-based modeling study, Netlogo was chosen as simulation software. First, a brief description of the modeling software is presented, which includes a small reflection on its usage and implication, next, the coding steps within the Netlogo application are discussed. Thereafter, the verification of the developed model is described along with each executed verification step.

5.4.1. Software

Netlogo is used as the main software package in which the model is built. Netlogo is a multi-agent programming language and modeling environment which is used for the simulation of complex adaptive systems which are characterised by complex social and natural phenomena (Tisue & Wilensky, 2004). The smart charging system and environment is a complex adaptive system. Netlogo is particularly useful for modeling these kind of systems, as it easily incorporates the states and actions used for the operation of agents. With respect to the goals of this thesis, Netlogo was designed for both educational and research applications.

5.4.2. Model verification

The created model should behave according to the defined conceptual model. To verify whether this is the case an evidence file was created. The full evidence file is presented in appendix C. According to Xiang, Kennedy, Madey, and Cabaniss (2005), multiple verification steps should be carried out chronologically, in order to identify whether the formalised model was correctly translated into an agent-based model. The process includes debugging software, filtering out incorrect implementation of formalised models and verification of the implemented calculations. Completing the verification process should ensure that any behaviour in the model is not contributed to mistakes made during the conceptualisation and formalisation.

According to (Macal & North, 2005), verification does not ensure that the model is useful, meets a set of model requirements and whether it accurately reflects the real world processes. Another important notion is that it is impractical to use all possible verification methods and execute them over the full range of possible model values. To that extent, a verified model is a model, which passed all selected verification tests. Furthermore, in the practices of this modeling research, verification was carried out throughout system modeling, therefore making it hard to track each verification step. Three verification steps have been executed to verify the model:

- Single-agent verification
- Interaction testing in a minimal model
- Multi-agent verification

5.5. Conclusions

Research sub-question 3: *“How can a model be developed, that gives insights in the short- and long-term effects of different design options regarding the fulfilment of ethical concerns and technology-usage?”*

Several consecutive steps were undertaken in order to create the agent-based model. The first step entails the operationalisation of the capability approach to retain focus on ethical values. The operationalisation was achieved by combining the CA with the four key constructs from UTAUT. This combined framework describes all interaction between EV owners and the system, creating a clear overview of the relation and the functioning of all system components. The second step revolves around quantifying the conceptual model. In order to achieve this, distributions for the conversion factors were derived from literature. Furthermore, a list of equations was created. The equations related to calculating effort-expectancy and performance-expectancy were logically derived from the theory on UTAUT. The equations for calculating the scores for the ethical values originated from the functioning of a smart charging system.

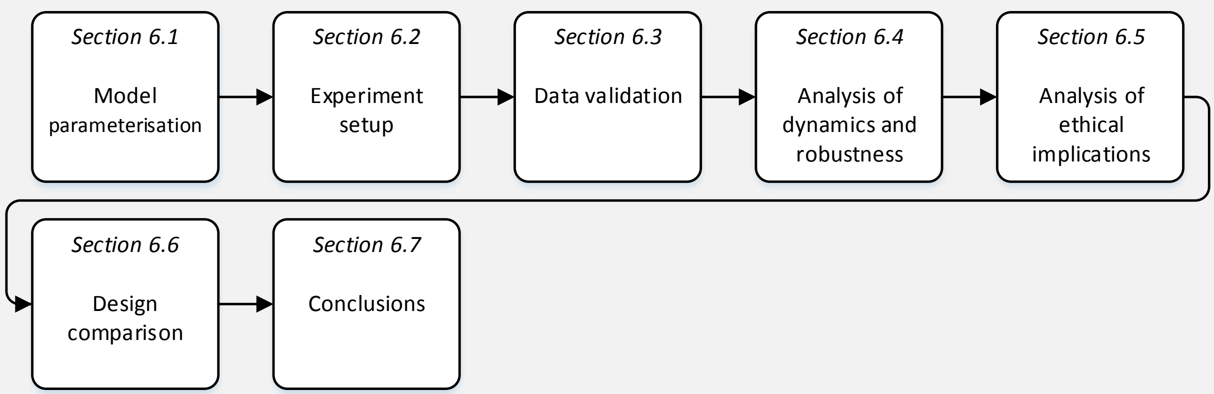
6. Experimentation and analysis

Structure

This chapter details the various steps concerned with model experimentation and data analysis. These steps provide essential insights in how the model behaves and how this behaviour can be translated to relevant findings regarding the main research question. Section 6.1 will detail the model parameterisation, regardless of the uncertain values concerning UTAUT, networking effects, and the CA. Due to the high uncertainty an exploratory modeling and analysis study is executed. Section 6.2 details the experiment setup used for model experimentation.

The model outcomes are separated in three groups: a group for data validation, a group for assessing the technological performance, and a group for assessing the ethical implications of each design option. Section 6.3 describes the data validation process with respect to the variables concerned with the different implemented model concepts. Section 6.4 will describe the system performance, dynamics, and robustness concerning number of users, number of transactions, and the quantity of traded kilometers on the platform. The last step of data analysis is assessing the ethical implications of each of the chosen design options. A description of this process is found in section 6.5.

The results from section 6.4 and 6.5 have been combined in section 6.6. This section aims at presenting a full overview of the effects of the different design options. A brief elaboration on the characteristics of each design with respect to the model outcomes is given. Section 6.7 concludes this chapter.



6.1. Model parameterisation

Residing on the concepts served as input for model creation, the model parameterisation identifies which factors are altered in order to create different experiments. This leaves for four distinct changeable parameters related to the technological layout of the system, namely: *Level-of-decentralisation, Data-storage-method, blockchain-configuration, consensus-protocol.* These four design options translate into different design alternatives.

Next to these parameters, two concepts related to the decision-making logic of UTAUT are altered, namely: *effort-expectancy,* and *performance-expectancy.* Effort-expectancy presents the agent's expected effort needed to operate the platform. Performance-expectancy is the individual expected performance of the system for a particular agent. These parameters are not-changeable from the offset but are expected to have an impact on the decision-making of EV owners.

6.2. Experiment setup

Computational experiments are used to examine the ranges of possible outcomes according to EMA practices. EMA is used to identify which technological layout is most robust under different possible scenarios. These scenarios were created by changing different uncertain values within the agent-based model. These uncertain values were identified after which an applicable range of values was chosen to differentiate. Lastly, A brief description on the identification of the technological design layouts is given.

6.2.1. Identification of uncertain values

Several uncertain variables were already identified throughout the thesis. Table 9 describes the different values and their corresponding representation within the agent-based model.

Within UTAUT, performance expectancy and effort expectancy are predictors of technology usage. However, the extent to which they determine technology usage differs among different technologies. It is therefore hard to predict which values correspond to the real-world agent behaviour. The model is constructed in such a way that a maximum performance of 1 can be achieved when an optimal design is initialised, all agents use the system, and the corresponding agent has maximum positive combination of conversion factors. This is however seldom the case.

The user absence compensation value represents a multiplier for decreasing the performance of the system when no system-users exist. The value is based on the notion that it is expected that system performance is lower when there are no system users.

Skill de-linearisation concerns the decrease of social influence as the skill of an EV owner increases. Different fundamental model properties affect the skill attainment of an EV owner. It is however unsure, how much the increase of skill contributes to the decrease of social influence. Furthermore, a multiplier, minimum skill attainment, is in place to balance the skill attainment. The sensitivity to this value remains unexplored and is therefore incorporated within the exploration. Minimum skill of users represents the minimum skill the EV owners within the model poses at model initialisation. Since no conceptualisation of skill regarding smart charging exists, it is hard to validate such a variable.

Within the capability approach, the conversion factors of EV owners each contribute to the EV owner being able to use the system, and whether the EV owner perceives added-value in using the system. These conversion factors are assumed to be equally important. In order to explore the sensitivity of the model when this is not the case a comparison variable is introduced to differentiate between the importance of system supply and personal charging pattern.

Affinity	*Uncertain variable*	*Netlogo parameter*
UTAUT	Performance expectancy	Performance_expectancy
	Effort expectancy	Effort_expectancy
	User absence compensation	User_absence_compensation
Social context	Skill attainment de-linearisation	Skill_delinearisation_value
	Minimum skill attainment	Min_skill_att_value
	Minimum skill of users	Minimum_skill
	Intelligence distribution	Intelligence_distribution

TABLE 9 UNCERTAIN MODEL VARIABLES USED FOR EMA

6.2.2. Identification of variable range for exploration

The uncertain values were explored according to the ranges presented in table 10. The ranges were selected according to the model balance. It is assumed that choosing a value beyond the exploration range results in non-usable data for model exploration.

Affinity	*Uncertain variable*	*Exploration range*
UTAUT	Performance-expectancy	[0.01 – 0.025]
	Effort-expectancy	[-0.5 – 0.3]
	User absence compensation	[0.1 – 0.9]
Social context	Skill attainment de-linearisation	[0.1 – 0.5]
	Minimum skill attainment	[0.05 – 0.2]
	Minimum skill of users	[0.1– 0.7]
	Intelligence distribution	[0.7 – 1]

TABLE 10 UNCERTAIN VARIABLES, EXPLORATION RANGE AND STEPS

6.2.3. Identification of technological design layouts

An EMA study was conducted on three distinct technological layouts. The layouts are presented in table 11. The first design layout remains close to a classical aggregator role which is centralised and stores generated data off-chain. The second design layout concerns a public decentralised blockchain platform on which participants can freely join. Data is stored on-chain and a proof-of-work mechanism is in place in order to protect transactional data and assets of monetary value. The third design layout is a decentralised blockchain on which participants are to be whitelisted. Therefore some power remains with the system operator.

Design	*Level of decentralisation*	*Data storage method*	*Blockchain configuration*	*Consensus algorithm*
Design layout 1	Centralised	Off-chain data storage	Private	Byzantine fault tolerance
Design layout 2	Decentralised	On-chain smart contracts	Public	Proof-of-work
Design layout 3	Decentralised	On-chain log events	Private	Proof-of-stake

TABLE 11 OVERVIEW OF DIFFERENT DESIGN LAYOUTS FOR EXPERIMENTATION

6.2.4. Model replications

Regarding the exploratory nature of this research, a higher number of scenarios is preferred over a higher number of replications. The model relies on a minimum number of agents to work properly. Lowering the number of agents within the model even further would hamper the representability of the model. It was therefore decided to keep the 200 implemented agents and execute 200 scenarios per design layout. Each scenario was replicated 5 times in order to cope with the stochasticity of the model.

6.2.5. Experiment analysis and model metrics

Several output metrics were used to analyse the model outcomes. Analysis of model outcomes is fundamental in deriving and defending research conclusions. All metrics used to evaluate the model outcomes are listed in table 12. The analysis process is split in four distinct sections. The first section serves as a validation step by assessing the different outcomes based on previously introduced concepts. The second step identifies the dynamic behaviour for each of the three design layouts for the variables concerned with performance and system usage. The third step is to assess the ethical value fulfilment for each of the three design layouts. Since the model outcomes regarding ethical value fulfilment are highly tentative, this section will involve reflection on the capability approach as well. The fourth and last section aims at drawing an overall comparison between the three design layouts based on the analysed experimental outcomes.

Metric type	*Metric*	*Netlogo reporter*
Metrics for validation	Mean skill of the users over time	Mean_skill_of_users
	Mean charging pattern of system users over time	Mean_charging_pattern_of_EVowners
	Mean social influence of EV owners over time	Mean_social_influence_of_EVowners
	Mean number of peers per user per day over time	Mean_peers_per_user
	Global social influence value	Social_influence_value
Metrics for robustness and dynamics	Total fraction of system users over time	fraction_of_system_users
	Total fraction of enabled EV owners over time	fraction_of_enabled_users
	Number of kilometers sold on the platform each day	Profitability_traded_kilometers
	Number of daily transactions	Profitability_transactions
Metrics for determining ethical value fulfilment	Privacy fulfilment	Privacy_score
	Trust fulfilment	Trust_score
	Security fulfilment	Security_score
	Confidentiality fulfilment	Confidentiality_score
	Anonymity fulfilment	Anonymity_score

TABLE 12 EXPERIMENTAL METRICS AND CORRESPONDING NETLOGO REPORTERS

The EMA workbench is setup to execute the different experiments from within python. The workbench was used to create scenarios across the whole exploration range displayed in table 10. All graphs used for experimental analysis are output of the EMA workbench and include 200 unique scenarios. Kernel Density Estimation (KDE) is used to present a smoothed visualisation of scenario outcome densities. Figure 31 shows an example of 200 scenarios as executed using the EMA workbench. The colored lines in the left box indicate the mean of 5 replications for a single scenario. The blue opacitated background indicates the envelope of the experiment. The envelope indicates the boundaries of all scenario runs. The right box shows the KDE output. This particular KDE plot was made at the last time step of the model run. It indicates the density of model outcomes at tick 200 regarding the value on the vertical axis. As can be seen in this example, most scenarios end up with a number of switches between roughly 300 to 800.

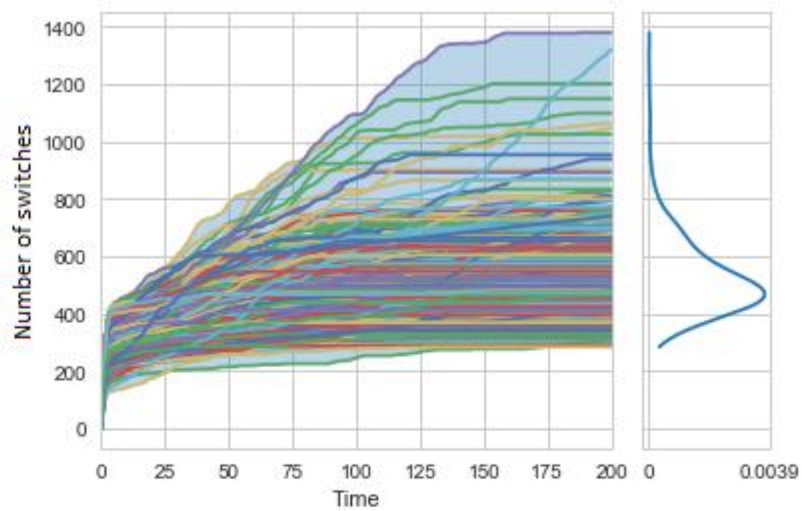


FIGURE 31 EXPERIMENT 1 EXAMPLE RESULTS LINES PLOT

Figure 32 was produced with the same data used in figure 31. The space between the two lines represent the envelope of the scenarios. The space between these two lines hold all 500 produced scenario results. Six dotted lines are vertically displayed in the envelope plot. These lines represent the points at which a KDE plot was produced. These KDE plots are displayed at the bottom of the figure. The multiple KDE plots help gain a better understanding of the actual behaviour of the scenarios by identifying patterns which most scenarios seem to follow. Furthermore, it places focus on the actual densities across the model run, instead of solely focusing on the end results.

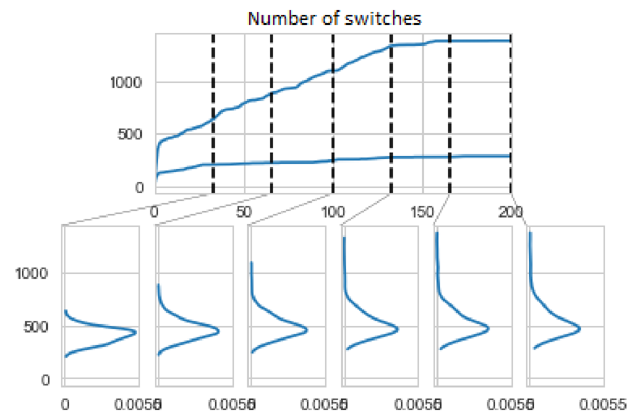


FIGURE 32 EXPERIMENT 1 EXAMPLE RESULTS MULTIPLE KDE

6.2.6. Experimental outcomes

This section is concerned with describing the experimental data. The experimental data was acquired in compliance with the described experimental setup in this chapter. As previously described, the data analysis process, as presented in figure 33, is executed. The data analysis process consists of 4 consecutive steps. Step one describes an attempt at model validation by comparing actual versus expected variable behaviour. Step two is concerned with the analysis of the dynamics and robustness of the three separate design layouts. Step three provides a methodological analysis and reflection on the possible ethical implications for each design layout. The last step compares the design layouts based on the outcomes of step one, two, and three.

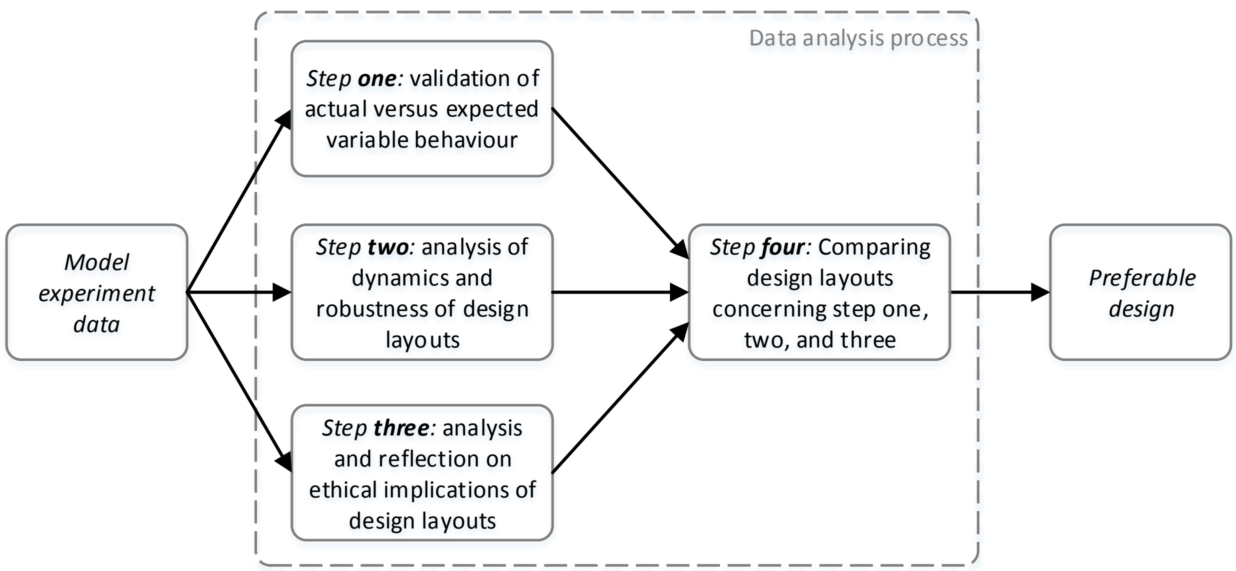


FIGURE 33 OVERVIEW OF DATA ANALYSIS PROCESS

6.3. Data validation

When a model is designed which is hard to validate, as is the case with this model, focus should be placed on validating the different concepts implemented in the model (Augusiak, Van den Brink, & Grimm, 2014). A data validation step is made by analysing the behaviour of variables identified by the different model concepts. The actual behaviour is compared to the expected behaviour. The aim is to identify whether the actual behaviour and expected behaviour are similar, and if not, why this occurred. The starting point is to identify what is to be expected in a real world scenario in which EV owners behave and change according to the principles and concepts identified in this thesis. For data validation experimental setup 1 is used unless noticeable differences regarding the behaviour of the plots exist between all three experimental setup. For the sake of reproducibility of model outcomes, an overview of all experimental outcomes including the plots for data validation is presented in Appendix E. The concepts, corresponding references, and corresponding variables presented in table 13 have been validated.

Concepts	*Data references*	*Validation variable*
Skill increase of EV owners	(Ramamurthy et al., 1992), (Witherspoon, 2017), (Czaja et al., 2006), (Luthra et al., 2014), (Palm & Hansson, 2006)	Skill_increase_of_EVowners
Charging pattern of EV owners	(Franke & Krems, 2013)	Mean_charging_pattern_of_users
Social influence	(Venkatesh et al., 2012), (Robeyns, 2006), (Hall & Khan, 2003)	Mean_social_influence_of_EVowners Social_influence_value
Peers per user	[Combination of concepts]	Mean_peers_per_user

TABLE 13 CONCEPTS FOR DATA VALIDATION INCLUDING DATA REFERENCES AND VALIDATION VARIABLES

6.3.1. Skill increase of EV owners

A gradual increase of the skill level of EV owners is expected when the system is being used. In accordance to the social network effects this increase should be related to the number of users and the overall skill level of the EV owners. Network effects decrease as the level of skill increases. Therefore, it is expected that as the skill level of EV owners gets higher, the increase of skill flattens out. This could partially be mitigated by an exponential growth in user numbers.

Figure 34 presents a multiple KDE plot of 200 scenarios of the mean skill level of all EV owners for experiment 1. The initial differences in skill are caused by the stochastic variation between scenarios. After initialisation it is noticeable that the scenarios show an initial increase of skill. This increase gradually flattens out and the scenarios tend to converge as time advances. This converging behaviour is logically derivable from the way networking effects are implemented. Scenarios with a lower skilled population tend to increase faster due to higher network effects. This effects occurs vice versa for higher skilled populations. The scenarios tend to converge towards a single point as time progresses.

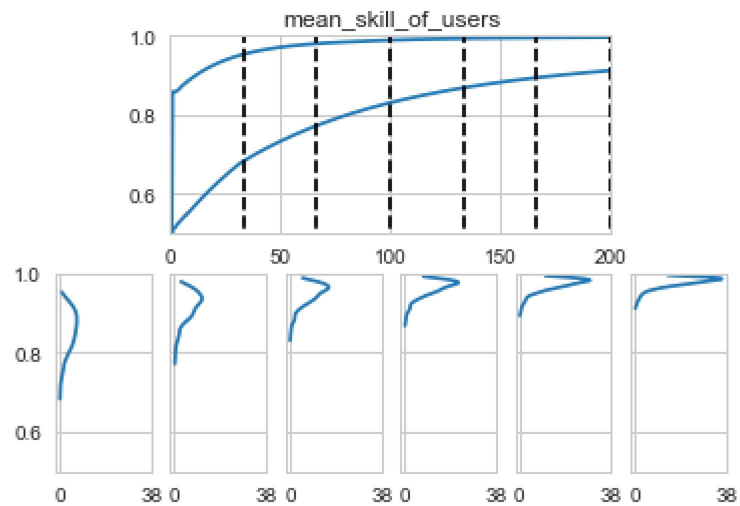


FIGURE 34 EXPERIMENT 1 MEAN SKILL OF USERS

6.3.2. Mean charging pattern of EV owners

The differences in charging patterns between EV owners, determine the overall personal performance of the system. It is expected that lower charging patterns, i.e. individuals that charge their EVs at a low charge level, are more compliant to start using the system. Higher charging patterns, i.e. charge whenever possible, generally need more system users to gain added-value of a smart charging system. The expectation is that the mean charging pattern of system users gradually increases as more users start using the system.

Table 14 Presents the multiple KDE plot for both experiment 1 and 2. Both experiments are visualised as their comparison gives a better overview of what is happening in the system. For experiment 1, no clear increase in charging pattern is noticeable. There is a logical reason for this behaviour. The mean charging pattern of the users participating on an optimal system should be near 0.5. The performance of a system gets maximised when the higher level charging patterns are compensated by lower level charging patterns. When the mean charging pattern of the system dips below 0.5, EV owners with a higher charging pattern are more likely to start using the system and vice versa. This causes the system to balance out at a mean charging level of 0.5. As indicated, experiment 1 immediately balances out at the optimal value of 0.5.

Reflecting on the KDE plots for experimental setup 2, it is clear that this system design is not optimal as the mean charging pattern remains below the optimal value of 0.5 for the entirety of the model run. It can be observed that most scenarios converge towards a mean charging pattern of around 0.45. After the initial increase the behaviour remains linear. An explanation for this result is that experimental setup 2 initiates a system which has a lower overall system performance. When the performance expectancy of an EV owner is established, a lower value of system performance results in a lower performance expectancy. The lower the charging pattern of this EV owner, the higher added-value the system has. The lower charging pattern and lower system performance level out, resulting in EV owners with lower charging patterns having a higher chance of entry, resulting in a lower mean charging pattern.

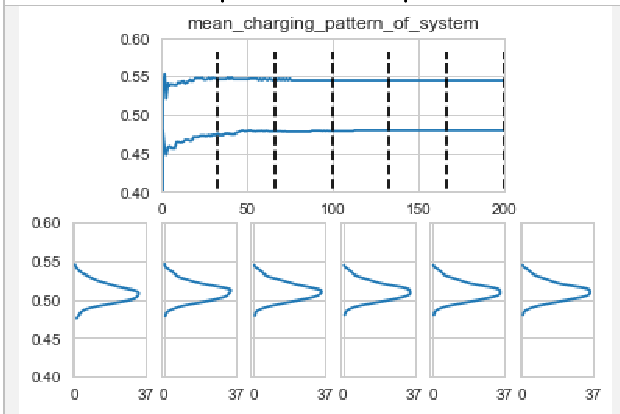
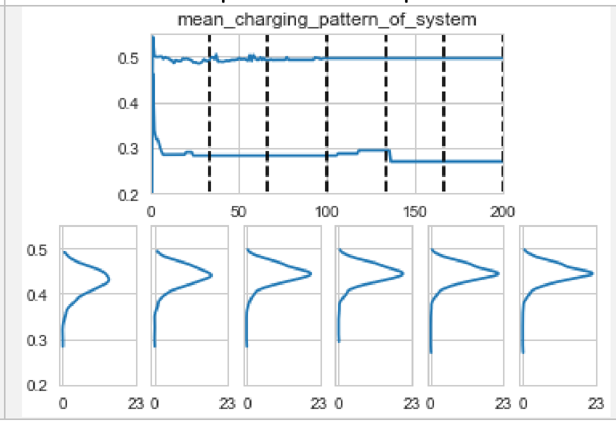
Experimental setup 1	Experimental setup 2
	

TABLE 14 MEAN CHARGING PATTERN OF SYSTEM FOR EXPERIMENTS 1 AND 2

6.3.3. Mean social influence of EV owners and global social influence

Social influence is determined by various factors, including the skill and charging patterns of all EV owners that use the system as well as the skill of the EV owner itself. In accordance to the described concepts, the social influence value of the system should increase when the number of higher skilled users in the system increase. However, this effects could potentially be mitigated by the differences in charging patterns as well as the decreasing effects of social networking effects as presented by Hall and Khan (2003). Furthermore, as the overall skill increases, EV owners become less prone to social influence.

Table 15 presents the multiple KDE plots for both the mean social influence of EV owners and the global social influence value. The global social influence value increases noticeably. This is caused by an increase in both the number of system users as well as their skill level. As expected, the scenario plots show behaviour similar to that of the skill increase and the number of system users. The overall social influence on the EV owners however, seems to decrease towards 0. Two concepts cause this behaviour: (1) the decreasing network effects and (2) the overall increase of skill. The network effects are implemented as a parabolic function, causing a steep climb of the global social influence when more users start to use the system. At a certain point in time the threshold for maximum social influence increase is met from which on the social influence value will start to flatten out. Secondly, the increase of skill of EV owners cause them to be less affected by social influences causing a further decrease of social influence.

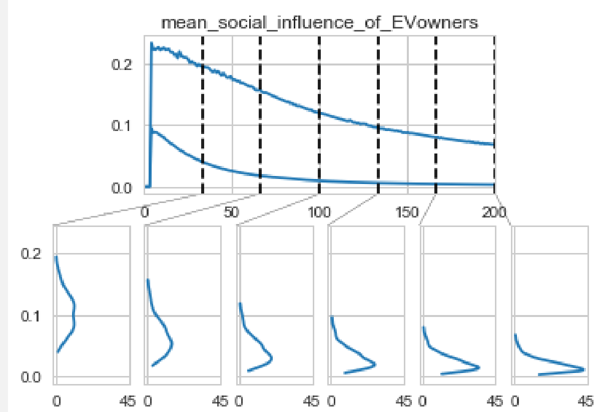
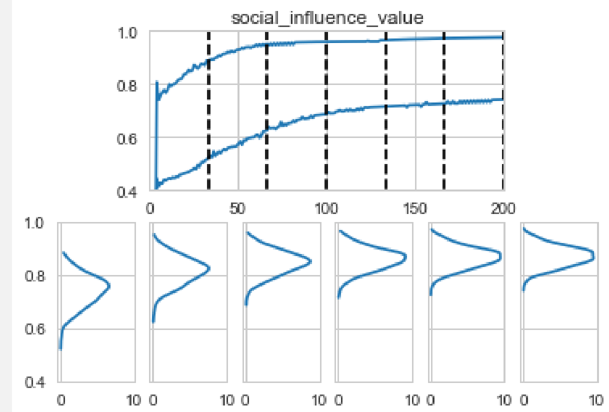
Experiment 1 - Social influence of EV owners	Experiment 1 – Global social influence value
	

TABLE 15 EXPERIMENT 1 RESULTS - SOCIAL INFLUENCE VALUE AND GLOBAL SOCIAL INFLUENCE

6.3.4. Mean number of peers per user

As the mean of charging-patterns increases, the surplus of electricity supply decreases. Therefore, the number of EV owners needed to fully charge an EV increases. It is therefore expected that the number of peers needed to fully charge an EV increases over time.

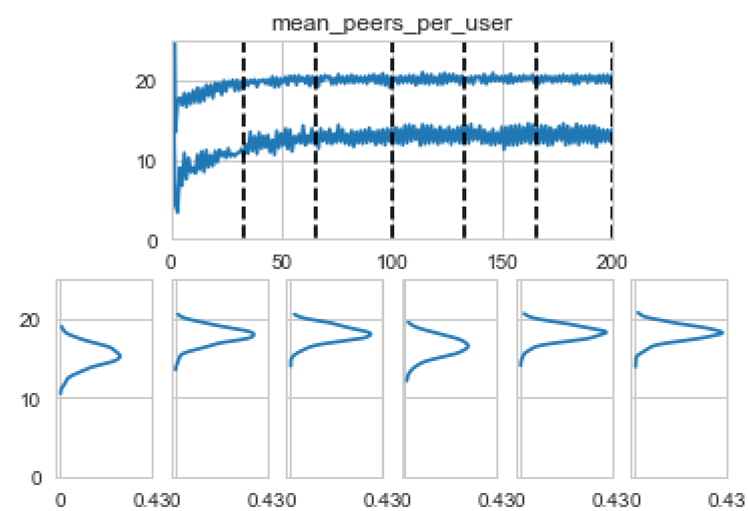


FIGURE 35 EXPERIMENT 1 RESULTS - MEAN PEERS PER USER

As can be seen from figure 35, the number of peers each user needs to fully charge its EV increases and stabilises. The dip which is observable in the KDE plots is caused by the constant oscillating behaviour. The oscillations in the scenario plots are caused by the constant value for daily driving distance of EV owners, which results in a constant shift between supply and demand of electricity and therefore the amount of available electricity. The increase in the number of peers is related to the aforementioned increase of the number of system users with a higher charging pattern. Imagine an EV owner with a charging pattern of 0.8. This EV owner will charge its EV when its EV-charge drops below 80% charge. When the EV owner has fully charged its EV, this EV owner is willing to sell a maximum of 20% EV-charge. This 20% Ev-charge might not be enough for other EV owners to fully charge their EV, resulting in an increase of transaction peers.

6.4. Analysis of dynamics and robustness

This section is concerned with describing the analysis of the dynamics and robustness of the variables concerned with system usage and overall system performance. These variables are mainly aimed at describing performance metrics with respect to robustness. Within this thesis, robustness is interpreted as stable behaviour which has low deviation between different scenarios. For each experiment, four experimental outcomes are described and interpreted. These outcomes are: (1) the traded kilometers on the platform, (2) the number of transactions, (3) the fraction of system users, and (4) the fraction of enabled users.

6.4.1. Outcomes experiment 1

Experiment 1 represents a design layout with a centralised system layout which stores data off-chain. Table 16 presents two graphs for the number of traded kilometers on the platform. As can be seen from the lines plot, high oscillations occur. These oscillations are caused by the constant changes in demand and supply. Whenever an EV owner charges its electric vehicle, which mostly occurs at a daily basis, the demand for electricity decreases and the potential supply increases. This phenomenon tends to create large fluctuations in the number of kilometers that are traded each day. As presented in figure 36, These oscillations don't seem to level out but rather create an oscillating behaviour for the entirety of scenarios. Therefore, the KDEs presented in table 16 are less interpretable. The mean of the oscillating pattern lies somewhere near 6000 for the majority of the scenarios.

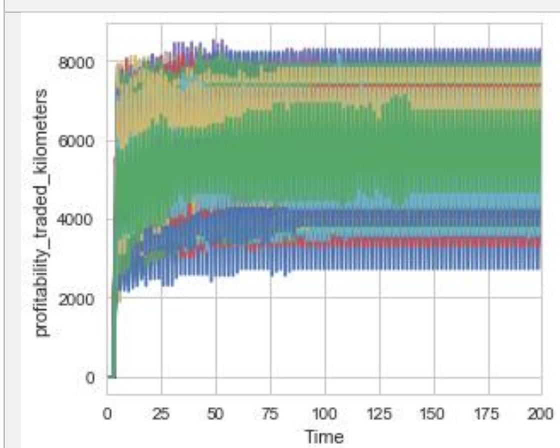
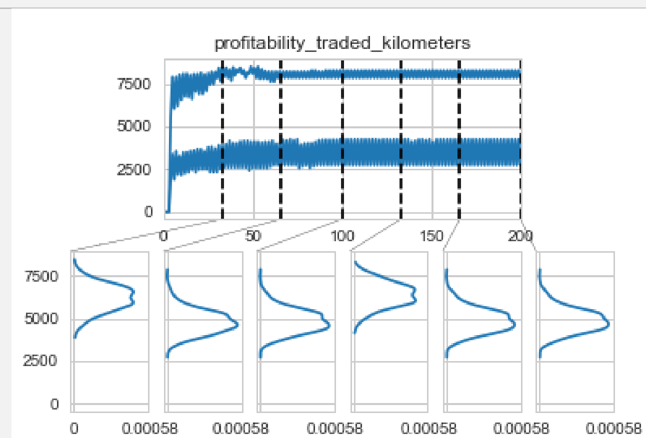
EMA lines plot – Traded kilometers	EMA multiple KDEs – traded kilometers
	

Table 16 Experimental results - Experiment 1 - Performance regarding traded kilometers

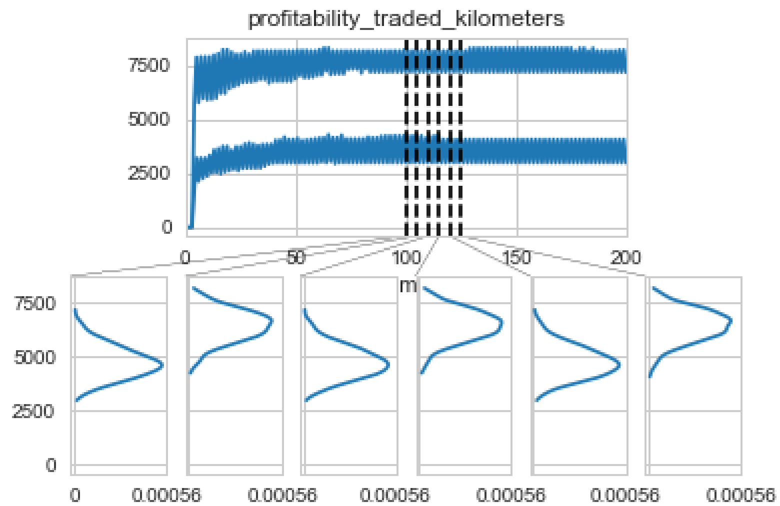


FIGURE 36 EXPERIMENTAL RESULTS - EXPERIMENT 1 - ANALYSIS OF TRADED KILOMETERS

Table 17 presents the outcomes for the daily number of transactions. A balancing increase is observable at the beginning of the model run. The KDE plots show that this increase is observable across a large range of scenarios. The most straightforward explanation for this behaviour is the steady increase of system users. The same type of oscillations are observable as with the number of traded kilometers. This similarity is caused due to the direct relation between the number of transactions and the number of traded kilometers. Figure 37 clearly indicates that these oscillations don't level out, but occur analogous for a large portion of scenarios. Therefore, an oscillation is observable in the KDE plots as well.

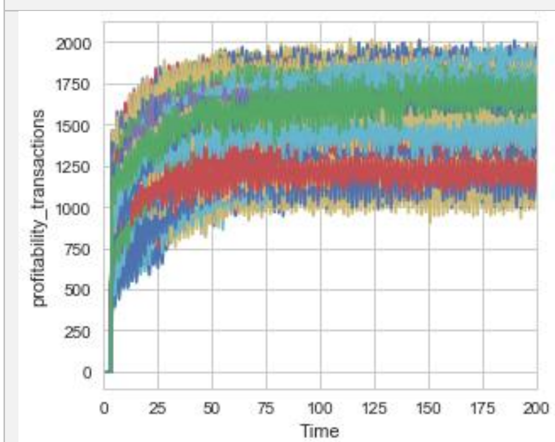
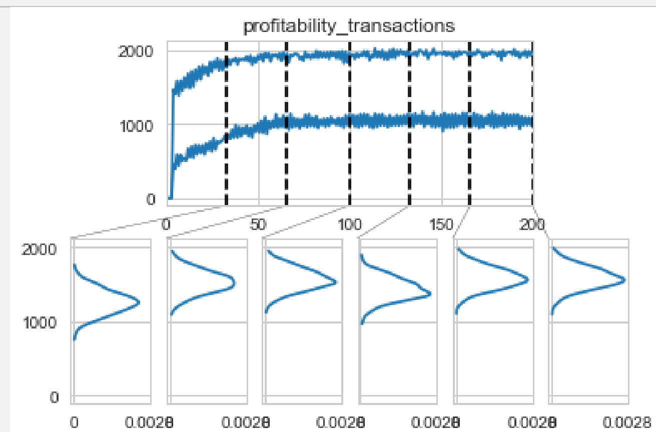
EMA lines plot – number of transactions	EMA multiple KDEs – number of transactions
	

TABLE 17 EXPERIMENTAL RESULTS - EXPERIMENT 1 - PERFORMANCE REGARDING NUMBER OF TRANSACTIONS

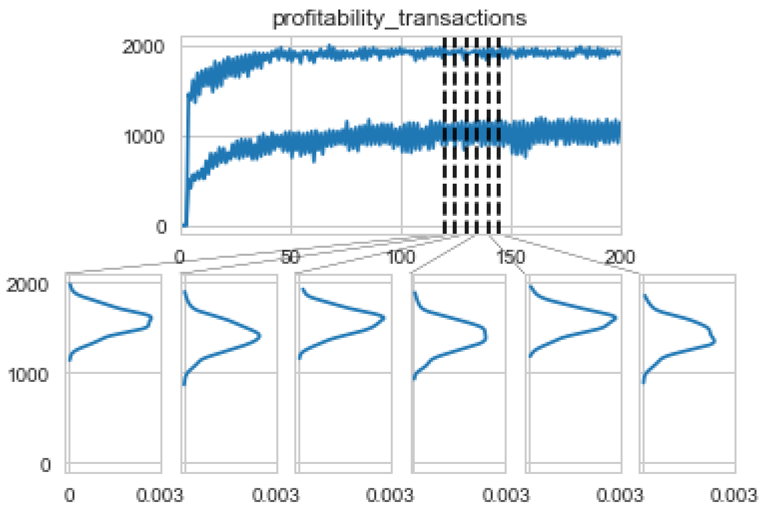


FIGURE 37 EXPERIMENTAL RESULTS - EXPERIMENT 1 - ANALYSIS OF TRANSACTIONS

Table 18 presents which fraction of initialised EV owners ends up using the smart charging system. The lines plot indicates a stabilising increase. Reflecting on the multiple KDEs, this behaviour is similar for most of the scenarios, and little deviations from this behaviour are present. After a certain point in time, the behaviour becomes linear, resulting in a constant fraction of system users. Most scenarios end up with a user fraction between 0.4 and 0.5 with a clear peak at roughly 0.45.

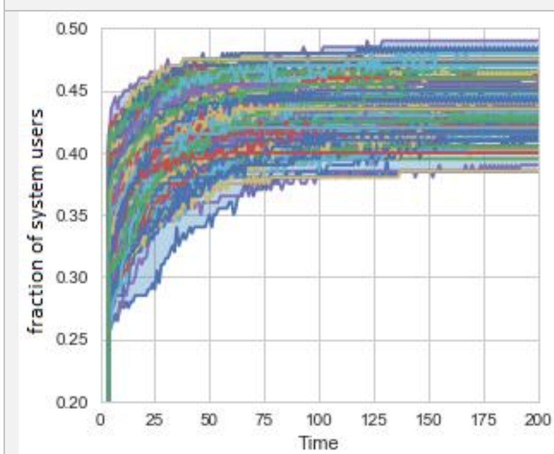
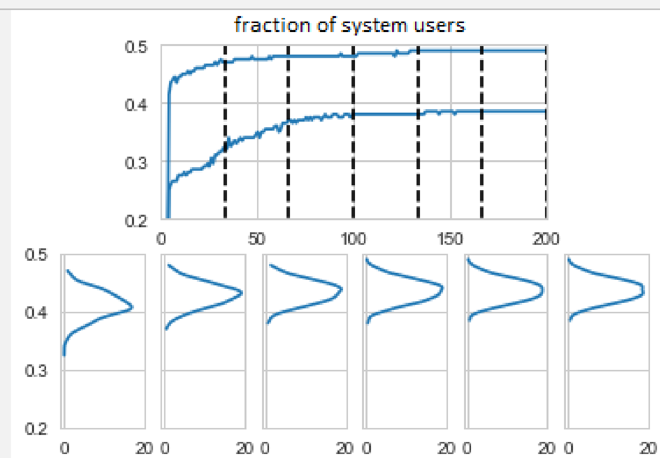
EMA lines plot – fraction of system users	EMA multiple KDEs – fraction of system users
	

TABLE 18 EXPERIMENTAL RESULTS - EXPERIMENT 1 - FRACTION OF USERS

Table 19 presents which fraction of initialised EV owners is enabled to use the system. It represents whether the skill level of the EV owners is high enough to use the system. It can be concluded that most scenarios result in a high fraction of enabled EV owners. Observing the KDE plots, it is clear that most scenarios come close to the maximum fraction of 1. It is noteworthy that the behaviour levels out towards the maximum enabled fraction of 1, indicating that a small number of EV owners is harder to enable. These EV owners have levels of skill and intelligence on the extreme ends of the normal distribution. It is promising that, under the chosen parameterisation, there are no scenarios deviating from the observed behaviour.

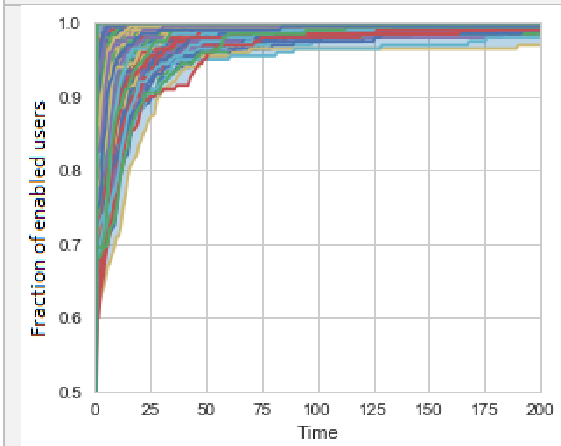
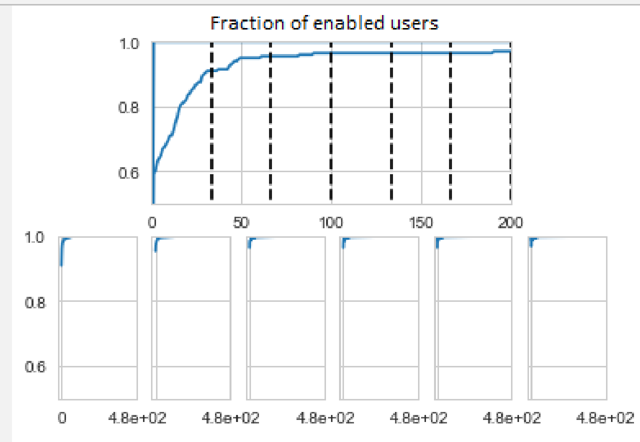
EMA lines plot – fraction of enabled users	EMA multiple KDEs – fraction of enabled users
	

TABLE 19 EXPERIMENTAL RESULTS - EXPERIMENT 1 - FRACTION OF ENABLED USERS

6.4.2. Outcomes experiment 2

The results of experiment 2 are elaborated on in this section. Experiment 2 is a decentralised platform with on-chain data storage through smart contracts. Table 20 presents the outcomes for the number of traded kilometers for experiment 2. The scenarios show linear behaviour with small oscillations. These oscillations are, similar to experiment 1, caused by constant changes in demand and supply of the system. These changes increase or decrease the possibilities to buy kilometers from the platform. Apparently, these oscillations are of a lesser degree as compared to experiment 1. Observing the multiple KDEs of all the scenarios, it is clear that an overall linear behaviour can be observed. A small increase of traded kilometers is observed in the first 100 ticks. This is caused by a number of factors such as the increase of the number of system users, the increase of system performance, and the increase of skill of EV owners leading to less effort needed to use the system. For experiment 2, the largest portion of scenarios result in a number of traded kilometers somewhere between 2000 and 4000 kilometers, with extremes at 1000 and 5000 traded kilometers a day. This spread is considered quite significant.

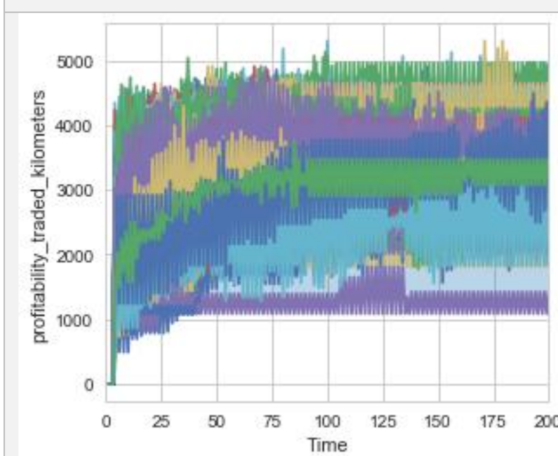
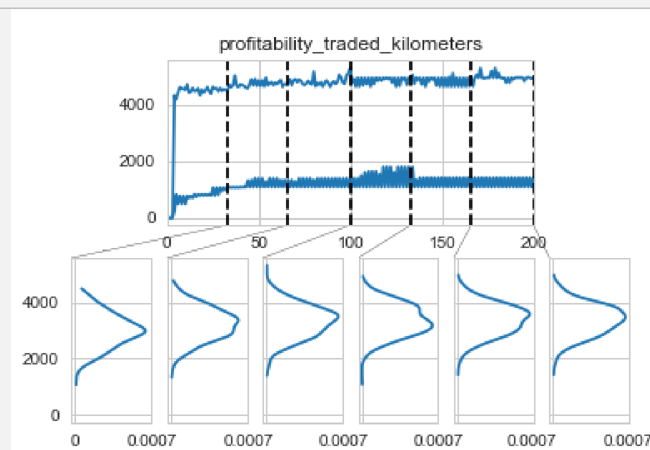
EMA lines plot – Traded kilometers	EMA multiple KDEs – traded kilometers
	

TABLE 20 EXPERIMENTAL RESULTS - EXPERIMENT 2 - PERFORMANCE REGARDING TRADED KILOMETERS

Table 21 presents the outcomes for the daily number of transactions on the platform. For most scenarios, the number of transactions increases in the first 100 ticks of the model run. The explanation behind this increase is two sided. First of all, as can be seen in table 22, most scenarios have an increasing number of users. More users result in more EV owners aiming at selling or buying kilometers on the platform. The second reason is more conceptual in nature. EV owners with higher charging patterns get a lower performance expectancy, as their charging behaviour fits less in a smart charging environment. These EV owners tend to start using the system in later stages, as system performance increases and the expected effort decreases. These EV owners aim to buy smaller portions of electricity, resulting in more transactions needed for an EV owner to sell all its electricity capacity. This should, logically, increase the number of peers needed to sell all available kilometers. Figure 38 shows this slight increase in mean number of peers per transaction. The behaviour is analogous with the increase in the number of transactions.

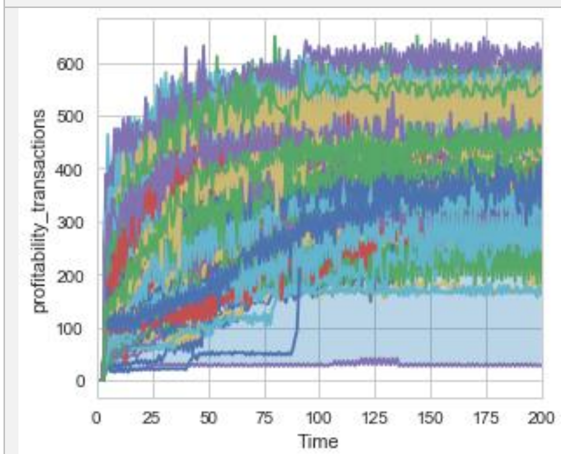
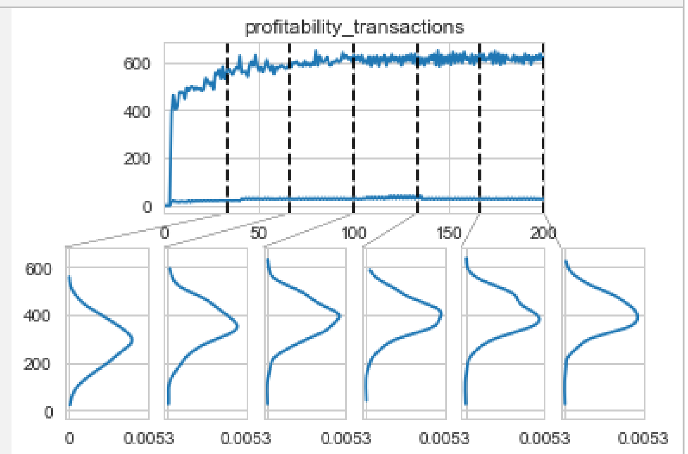
EMA lines plot – number of transactions	EMA multiple KDEs – number of transactions
	

TABLE 21 EXPERIMENTAL RESULTS - EXPERIMENT 2 - PERFORMANCE REGARDING NUMBER OF TRANSACTIONS

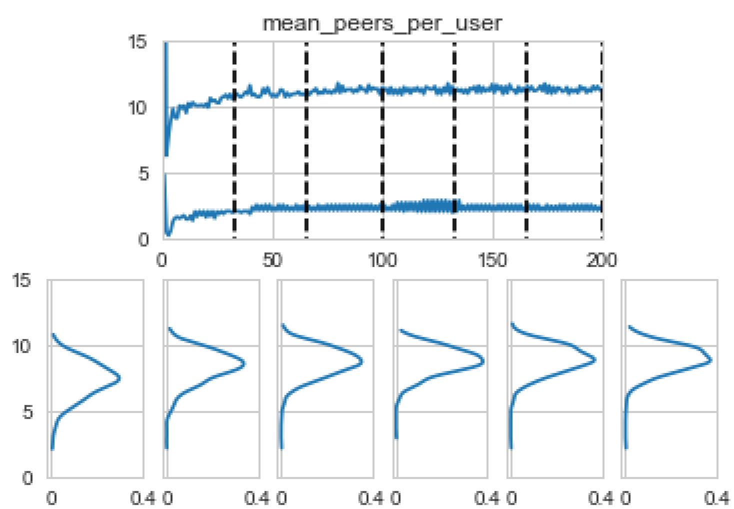


FIGURE 38 EXPERIMENTAL RESULTS - EXPERIMENT 2 - NUMBER OF PEERS PER USER

Table 22 illustrates the lines and KDE plots for the fraction of system users. Most scenarios tend to have increasing and stabalising levels of system users. The multiple KDE plot indicates that throughout the model run a narrow region covers most scenario outcomes. This region tends to become thinner over time. After tick 100 this region lies between a user fraction of 0.2 and 0.25. A clear outlier is distinguishable at the lower end of the lines plot. This outlier remains linear for the entirety of the model run. The same outlier is not clearly observable in table 23, indicating that this scenario has enough enabled users.

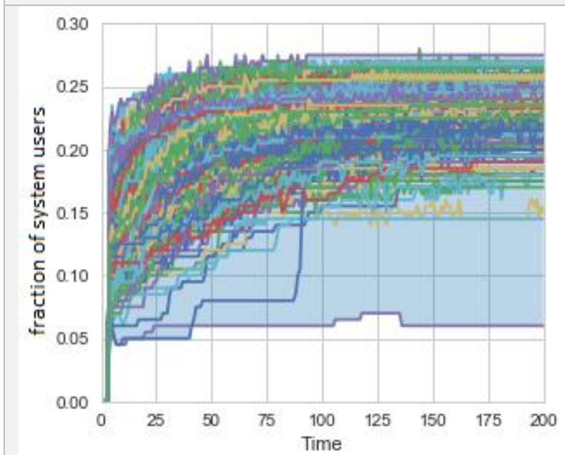
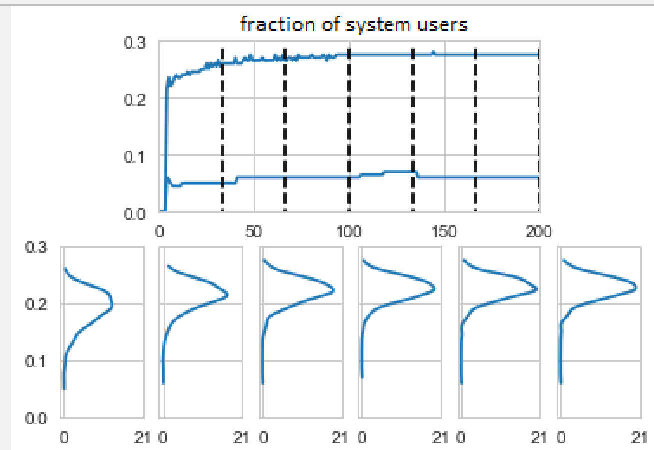
EMA lines plot – fraction of system users	EMA multiple KDEs – fraction of system users
	

TABLE 22 EXPERIMENTAL RESULTS - EXPERIMENT 2 - FRACTION OF USERS

With respect to the fraction of enabled users in the system environment, table 23 presents the lines plot and KDE plots. The fraction of enabled users increases at first but levels off the closer the lines get to the maximum value of 1. The KDE plots indicate that in time, the majority of scenarios get close to the maximum fraction of 1, indicating that most EV owners in the system environment are enabled to use the system.

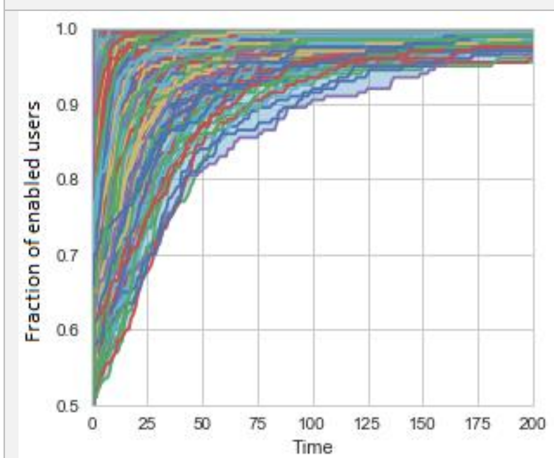
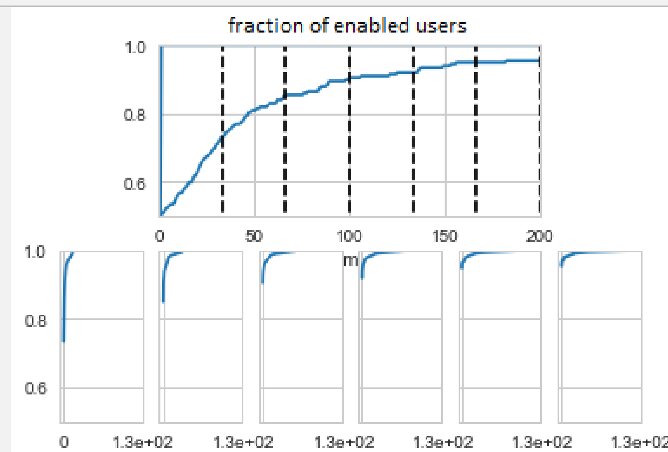
EMA lines plot – fraction of enabled users	EMA multiple KDEs – fraction of enabled users
	

TABLE 23 EXPERIMENTAL RESULTS - EXPERIMENT 2 - FRACTION OF ENABLED USERS

6.4.3. Outcomes experiment 3

The results of experiment 3 are elaborated on in this section. Experiment 3 is a decentralised platform with on-chain data storage through log-events. As presented in table 24 the number of traded kilometers has no abrupt increase or decrease. Aside from the observable oscillations, the scenarios retain stable levels of traded kilometers after tick 50. This indicates that no large changes occur with respect to the number of traded kilometers. Reflecting on the KDE plots, most scenarios have a traded kilometer value between 2000 and 5000, which is constant during the model run. Reflecting on what is observed, the experimental setup seems to result in stable system behaviour regarding traded kilometers.

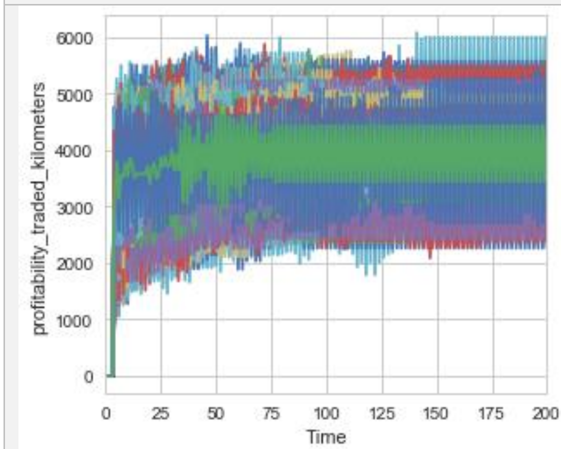
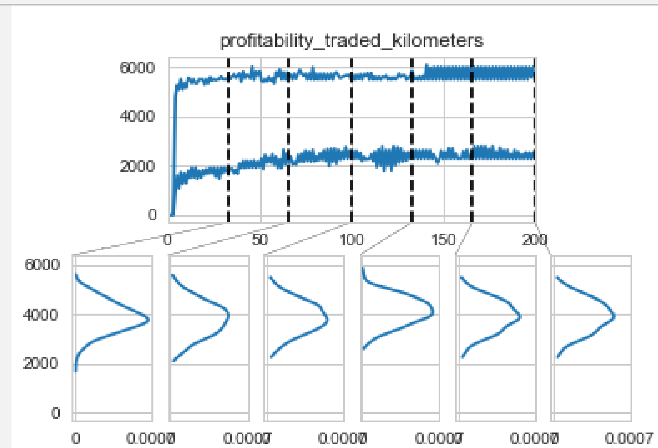
EMA lines plot – Traded kilometers	EMA multiple KDEs – traded kilometers
	

Table 24 Experimental results - Experiment 3 - Performance regarding traded kilometers

Table 25 presents the results regarding the daily number of transactions. Both the lines plot and the KDE plots indicate an increase towards a stable level of transactions. The KDE plots don't indicate that the scenarios tend to converge to the same level of transactions. The scenarios tend to follow the same pattern but end up with different numbers of transactions. After the first 100 ticks, the number of transactions remain stable for most of the scenarios.

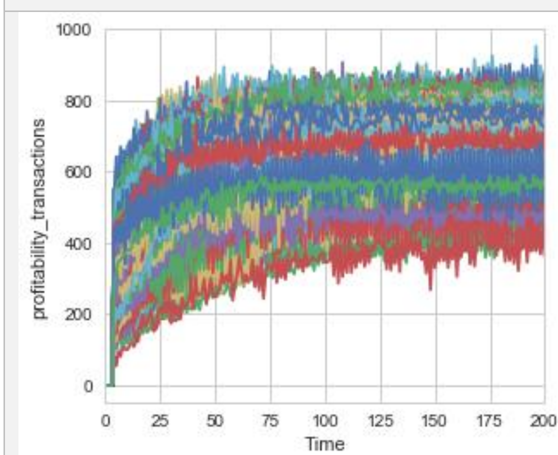
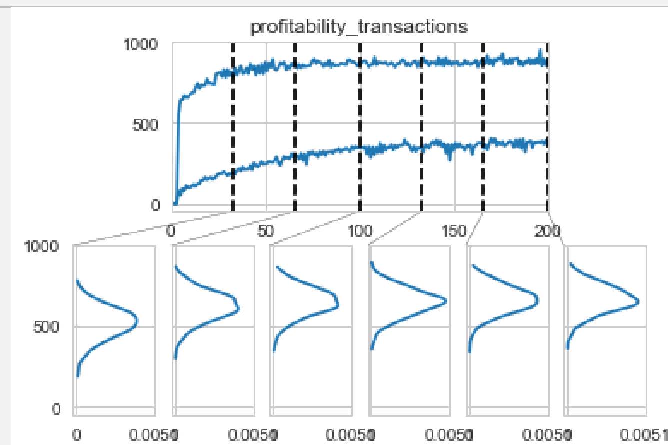
EMA lines plot – number of transactions	EMA multiple KDEs – number of transactions
	

Table 25 Experimental results - Experiment 3 - Performance regarding number of transactions

Table 26 Presents the lines plot and KDE plots for the fraction of system users. As can be observed from both the lines and KDE plots, the user fraction increases at first but decelerates towards stable behaviour. Most scenarios end up in a user fraction between 0.25 and 0.3. As the KDE plots indicate, the behaviour is roughly linear considering all possible scenarios. Indicating that, considering the model run length, the initiated scenarios quickly reach a balance. The initial increase of users can be appointed to the initial surge in skill and system performance. This allocates more added value to the system for specific system users, leading to an increase in user numbers.

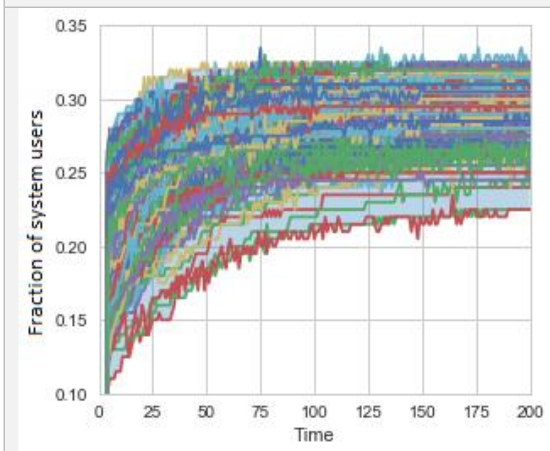
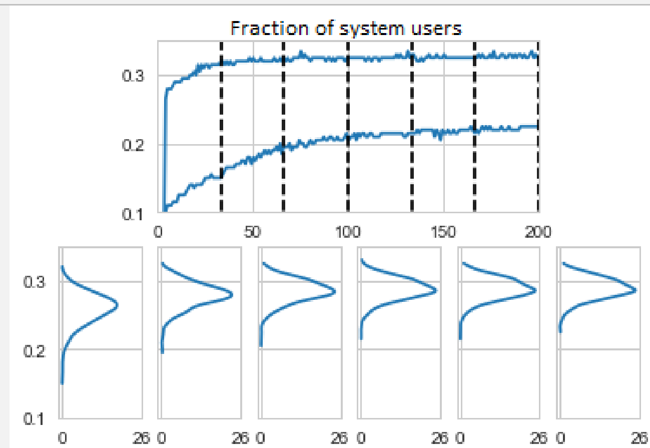
<table>
<tr><th>EMA lines plot – fraction of system users</th><th>EMA multiple KDEs – fraction of system users</th></tr>
<tr><td>
</td><td>
</td></tr>
</table>

TABLE 26 EXPERIMENTAL RESULTS - EXPERIMENT 3 - FRACTION OF USERS

Table 27 presents the outcomes regarding the fraction of enabled users. The fraction of enabled users, increases and levels out conformable to the fraction of system users. Most scenarios come close to the maximum enabled user fraction of 1. Few scenarios take a longer time to reach these levels. After tick 100, each scenario has an enabled user fraction higher than 0.9. The behaviour is quite similar to the behaviour observed for experiment 1 and 2.

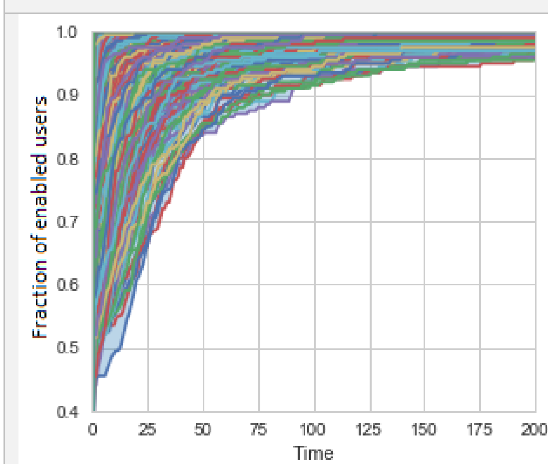
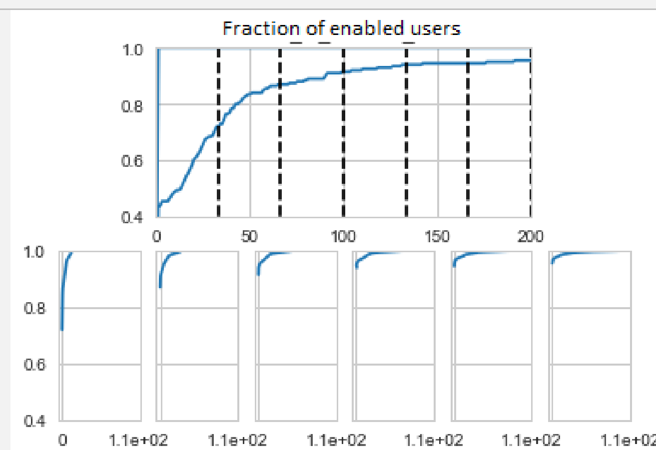
<table>
<tr><th>EMA lines plot – fraction of enabled users</th><th>EMA multiple KDEs – fraction of enabled users</th></tr>
<tr><td>
</td><td>
</td></tr>
</table>

TABLE 27 EXPERIMENTAL RESULTS - EXPERIMENT 3 - FRACTION OF ENABLED USERS

6.5. Analysis of ethical implications

This section is considered a delicate and important step towards understanding which ethical problems could arise over time. And more importantly, how they might differ between different designs. Achieving this insight helps understanding which particular groups of people will and will not use the system. A structural approach is used to aid defining these differences. The steps of analysis as presented in table 28 are proposed.

Step of analysis	*Insights*
Step 1: Theoretical interpretation	Link between CA and the outcomes of the model
Step 2: Data description	What does the data show
Step 3: Linking model and theory	How does the data compare to the CA
Step 4: Comparing designs	What are the differences between design layouts

TABLE 28 PROCESS OF ETHICAL IMPLICATIONS ANALYSIS

6.5.1. Step 1: Theoretical interpretation

Concerning the CA, the various functionings are in concept morally neutral (Robeyns, 2011). Thus for an EV owner to transact on the smart charging platform cannot be perceived of either being good or bad. However, the functionings itself are not univocally. They are perceived depending on the context in which these transactions are made and regarding the various underlying normative contexts.

The CA evaluates policies and change concerning their impact on the capabilities of people as well as their functionings. It was decided to split the capability of *transacting on a smart charging platform* across the five ethical value categories. This way, the capabilities became a tool for comparing which design enables the most freedom for individual users regarding different ethical values (Robeyns, 2011; Sen, 1993). As intended, this shapes room for synthesizing model outcomes with the normative concept of capabilities. The outcomes of the model tell something about the likeliness of possible ethical concerns. The numbers themselves are meaningless, but the relative performance concerning the three chosen design layouts are useful. This relative performance enables us to give an indication of which design best enables valuable functionings. First, capabilities are opened up for those capable in achieving them, i.e poses the right combination of conversion factors. Secondly these capabilities are to some degree ethically viable concerning the chosen design layout. This evaluation of designs is in line with the way the CA evaluates interpersonal comparisons.

The chosen interpretation of ethical values has certain limitations. The ethical concerns are identified as being equal for everyone. This notion crosses swords with the strong acknowledgement of human diversity. Human diversity is both internal; Person A might consider privacy less important than trust, and external; Person A might consider privacy less important than person B. Since ethical values are highly subjective and can't easily be operationalised, they are not implemented as conversion factors. The decision of considering ethical values as capabilities holds since considering them as capabilities disconnects them from the differences between people. Therefore, it tells us something about how technology deals with possible ethical problems rather than how people react to them. This has a huge impact on the interpretation strength of the results as it is unclear what ethical problems specific users might experience.

6.5.2. Step 2: Data description

The five value categories are elaborated on with the use of model output. The graphs associated with this section have a maximum value of 1 and a minimum value of 0. The fulfilment of ethical values will be referred to as *score* in this section. The model is created in such a way that a score of 1 is the optimal score. However, as stated earlier, the relative scores between the designs are much more useful. As has been presented in this thesis, some ethical values are highly related.

Data description experiment 1

Figure 39 presents the envelope plot and several KDEs for the privacy score of experiment 1. The initial value for privacy decreases towards a stable level. The decrease is caused by an increase of users, which leads to the system being more prone to privacy related issues. It is noteworthy that the privacy score for all scenarios lies between 0.675 and 0.750. Which is a small region. More importantly, the behaviour is linear and doesn't show abrupt increases or decreases. The distinct peak within the fourth KDE plot is caused by a sudden decrease of system users. This is caused by the constant fluctuating demand and supply causing users to constantly start and stop using the system.

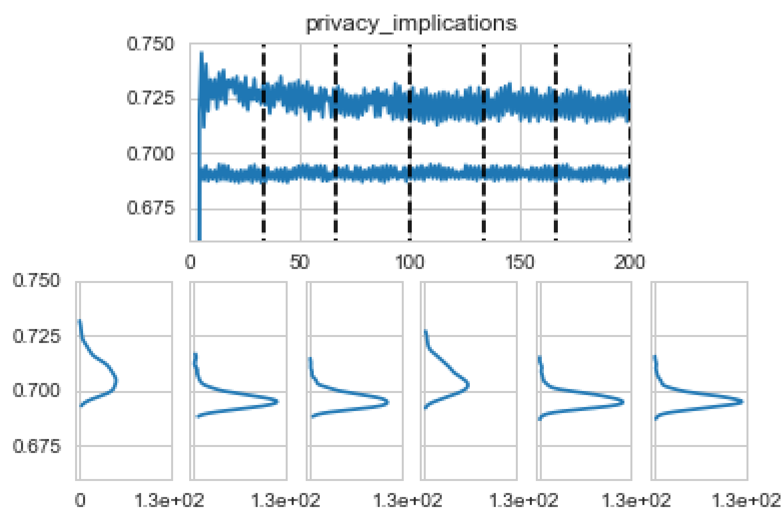


FIGURE 39 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 - PRIVACY SCORE

Figure 40 presents the outcomes regarding the security score. A gradual increase levels out towards stable behaviour. The gradual increase is caused by an increase of users, causing the consensus mechanism to better function. The increased functioning of the consensus mechanism enables the system to better protect the privacy sensitive data. However, the security score remains at the lower end of the scale for most scenarios. With the majority of the scenarios dipping just under a score of 0.10.

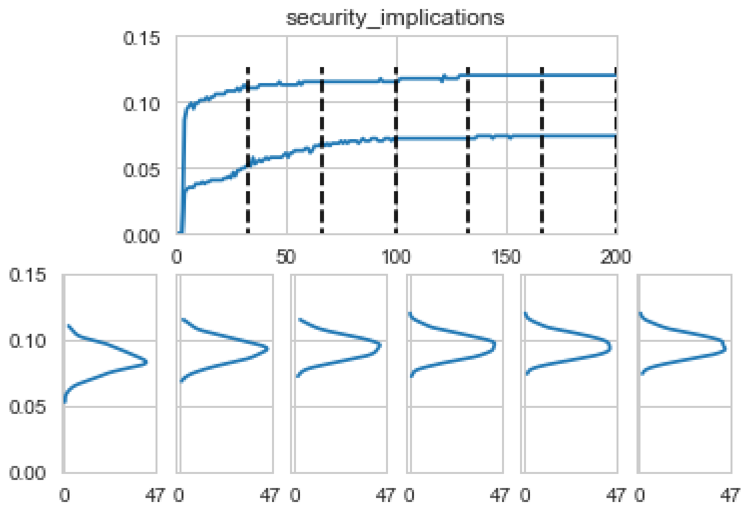


FIGURE 40 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 - SECURITY SCORE

Figure 41 presents the outcomes regarding the trust score. The KDE plots clearly show an increase in the trust score as time advances. As trust in the functioning of the technology is largely determined by the effectiveness of the system to safeguard private data, trust increases as the number of users increase. In time, the initial increase levels out towards linear behaviour in correspondence with the balanced number of system users. Each scenario has a projected trust score of above 0.8.

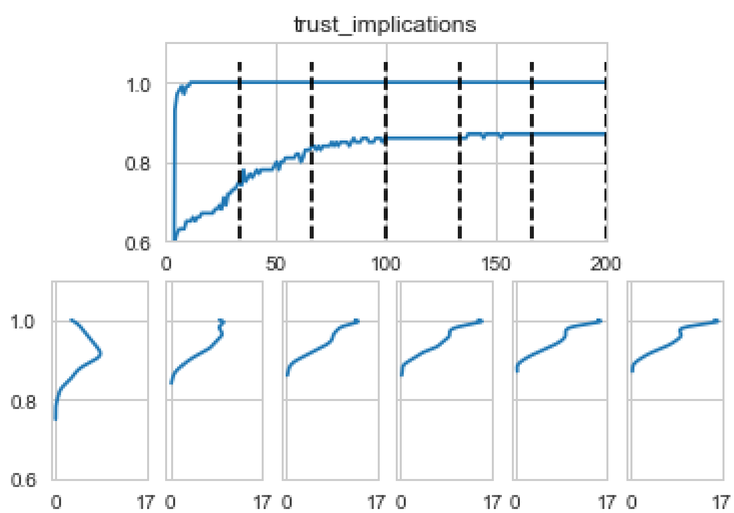


FIGURE 41 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 - TRUST SCORE

Figure 42 presents the outcomes for the anonymity score. Most scenarios start with an anonymity score of 0. Few scenarios briefly attain a positive trust score. During the model run, the trust score of these scenarios rapidly plummets towards 0. During the entirety of the model run, all scenarios retain an anonymity score of 0. The behaviour is caused by an inferior system design regarding fundamental properties, which has a larger effect on centralised systems. As described in chapter 5, the fundamental properties of the system cannot comprehend with the increased number of users. As the number of users grow, the anonymity score will decrease.

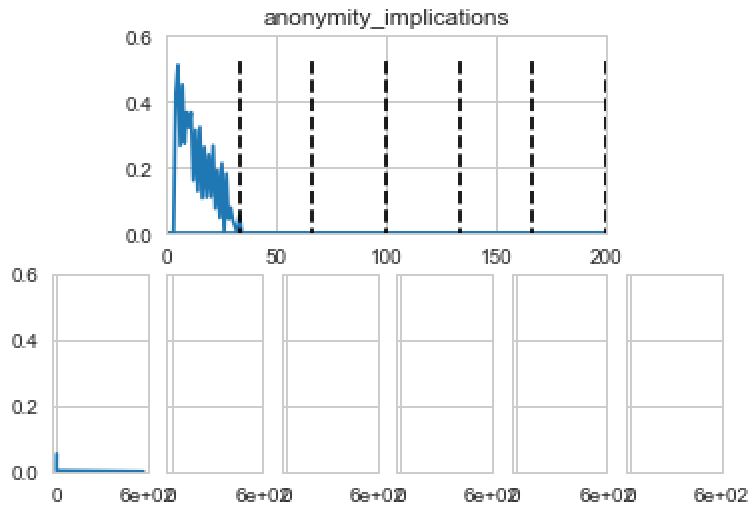


FIGURE 42 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 - ANONYMITY SCORE

Figure 43 Presents the outcomes for the confidentiality score. Straight after model initialisation, a decrease which levels out is observable. This decrease is caused by two main influencing factors. Primarily, the number of transactions and transaction peers on the platform increases, which causes an increase in the possibility for confidentiality issues. The second influencing factor is the comparison made with the number of transactions that occurred in the past. The total number of transactions keeps increasing, while the actual differences regarding transactions from day to day decrease. This causes the scenarios to converge as can be seen in the KDE plots.

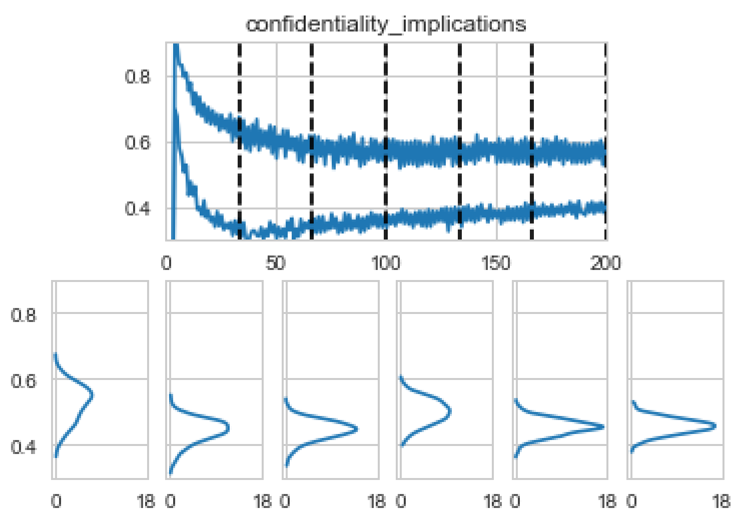


FIGURE 43 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 - CONFIDENTIALITY SCORE

Data description experiment 2

Figure 44 indicates the privacy score for experiment 2. Observing the KDE plots, the behaviour can be described as linear. It is noteworthy that as time advances, the scenarios tend to slowly converge towards the same privacy score, which is somewhere around 0.75. This phenomenon occurs due to the slow increase of system users over time. The number of users tend to balance out for each scenario. However, some scenarios need more time to reach this balance. More scenarios reach the corresponding privacy score, as more scenarios reach their optimal number of users. Furthermore, it can be noted that few scenarios reach a privacy score higher than 0.8. The envelope roughly reaches from 0.7 towards 0.85.

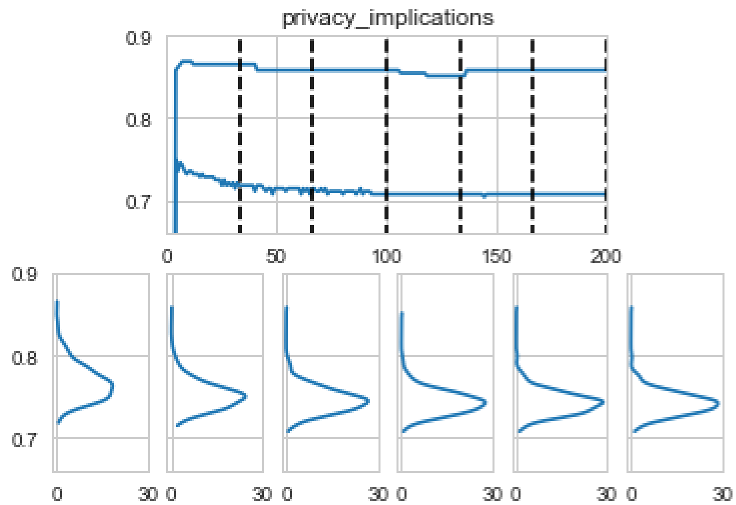


FIGURE 44 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 - PRIVACY SCORE

Figure 45 presents the outcomes regarding the security score. A gradual increase over time can be observed from the KDE plots. With the majority of the scenarios gradually increasing. The behaviour tends to become linear as time advances. The envelope of all scenario plots roughly lies between 0.3 and 0.4. Most scenarios end up with a security score between 0.35 and 0.4. The differences between most scenarios regarding the security score are therefore considered small.

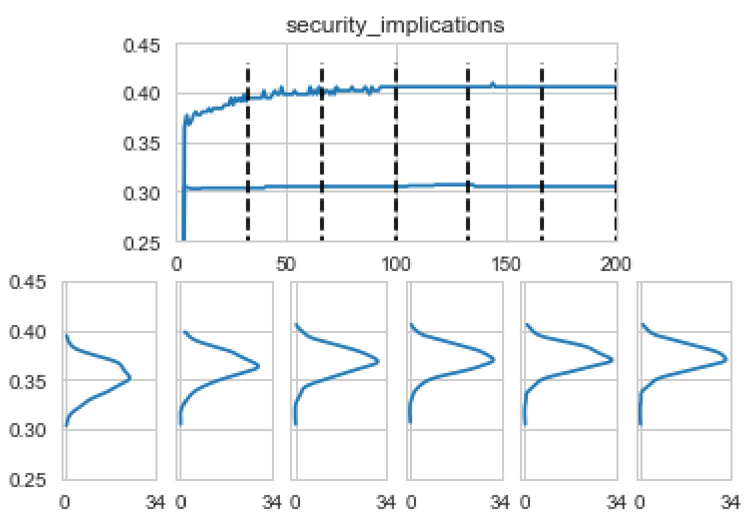


FIGURE 45 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 - SECURITY SCORE

Figure 46 Illustrates the outcomes regarding the trust score. After initialisation, a gradual increase is observable, after which the trust score levels out. Regarding all scenarios, no significant observable changes occur after tick 50. The KDE plots indicate that at a certain point in time, the score remains stable. Reflecting on the way in which trust is calculated, this stagnation is caused by the explored systems reaching stable numbers of system users. The trust score remains stable as these user numbers, on average, stop changing. Most scenarios are distributed around a trust score of 0.8 with an envelope between 0.7 and 0.9, with a few scenarios dipping under a trust score of 0.6 for the entirety of the model run.

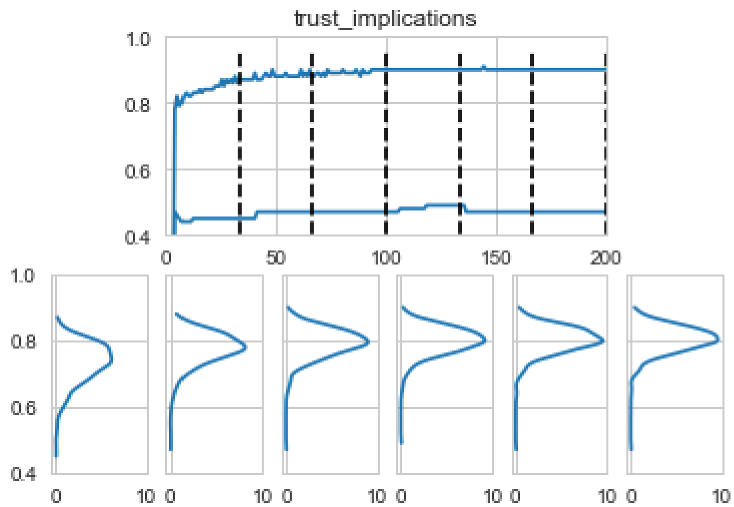


FIGURE 46 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 - TRUST SCORE

Figure 47 presents the outcomes concerning the anonymity score. As with the trust score, the behaviour is quite linear. There is a significant spread between the scenarios causing an envelope reaching from 0.7 to 1. Furthermore, the spread of scenarios roughly remains the same throughout the model run, implying that scenarios don't converge or diverge. For most scenarios, the anonymity score is between 0.75 and 0.9. Which is considered as high.

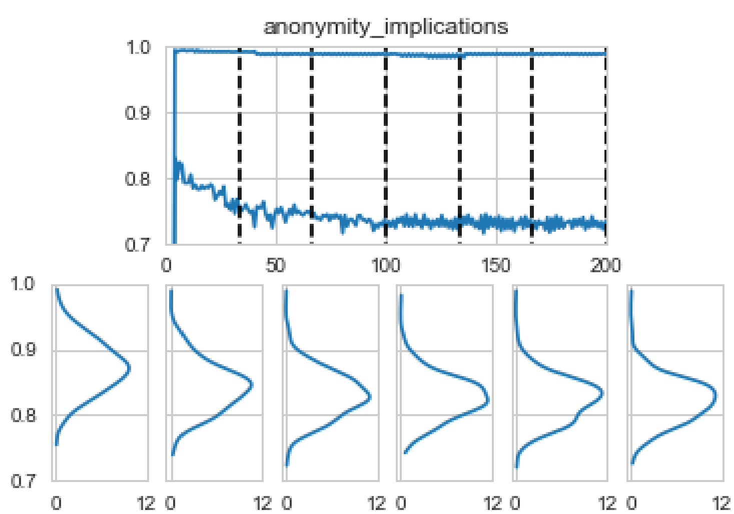


FIGURE 47 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 - ANONYMITY SCORE

Figure 48 illustrates the confidentiality score. The KDE plots indicate a small decrease in confidentiality score which levels out as time advances. Aside from a clear outlier, most scenarios converge towards the same confidentiality score of 0.75. The foundation of calculating the confidentiality score causes this phenomenon. The formula tends to reach an optimal value whenever the number of transactions on a certain day is equal to that of the day before. As explained in section 6.4.2, as time progresses, the number of transactions level out for most scenarios. Therefore, the daily differences in number of transactions decrease over time, resulting in most scenarios converging towards the same confidentiality score.

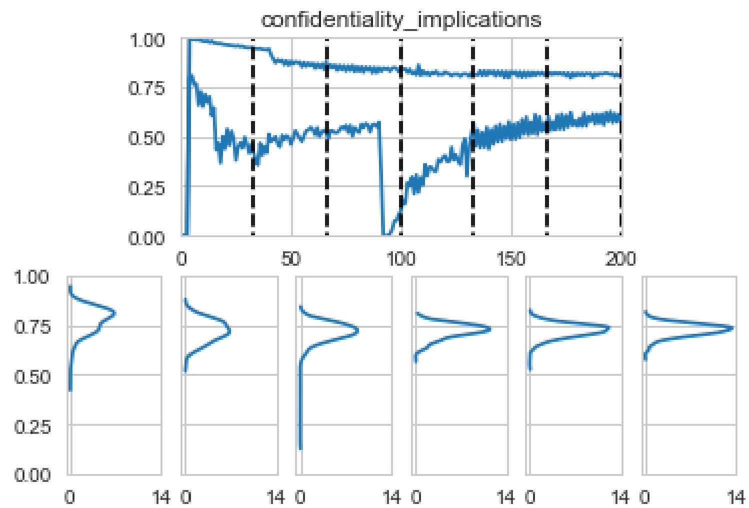


FIGURE 48 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 - CONFIDENTIALITY SCORE

Data description experiment 3

Figure 49 presents the outcomes concerning the privacy score for experiment 3. A decrease from the initial privacy score towards a stable level Is observed. Furthermore, the scenarios slowly converge towards the same privacy score of 0.65. A few scenarios produce privacy scores higher than 0.7. However, in time, these scenarios dip under a privacy score of 0.7 as well.

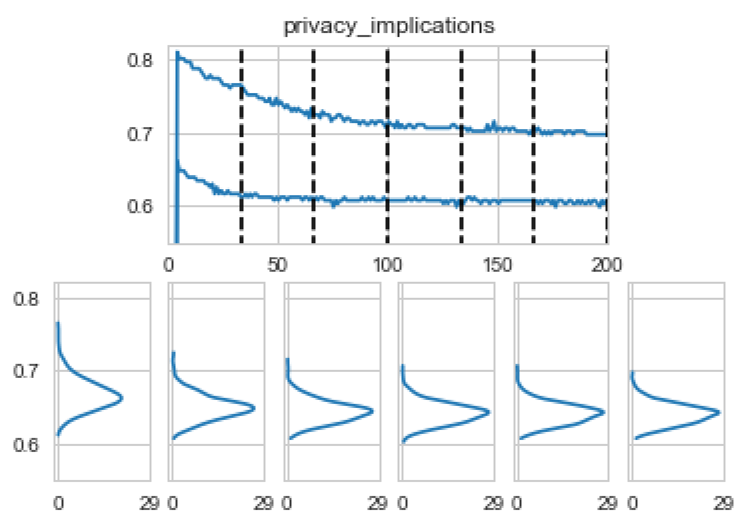


FIGURE 49 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 - PRIVACY SCORE

Figure 50 Presents the outcomes regarding the security score. An increase in the security score is observable over time. However, this score gradually flattens out and becomes linear. Most scenarios end up with a security score between 0.4 and 0.45. Few scenarios end up with a security score lower than 0.4. The security score is affected by three variables, of which 2 are the same for each scenario within a certain experimental design. The effectiveness of the consensus algorithm is the factor influencing how the security score advances over time. Since this value depends largely on the number of users, the differences between scenarios are caused by a difference between the number of users.

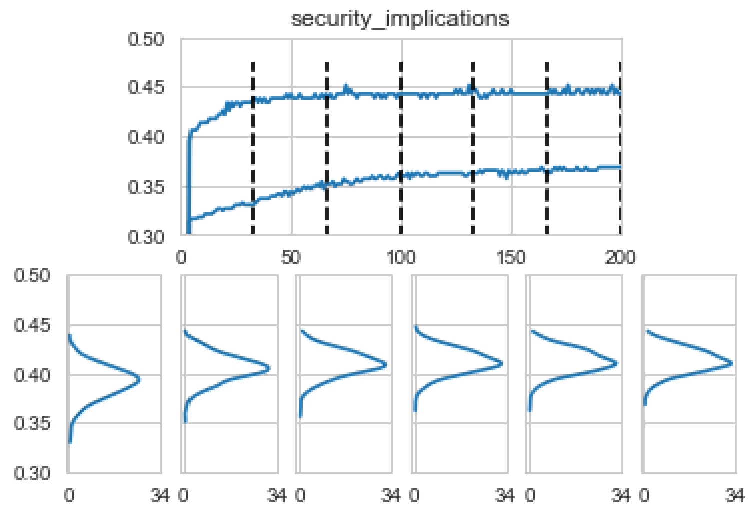


FIGURE 50 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 - SECURITY SCORE

Figure 51 presents the outcomes regarding the trust score. An initial increase results in linear behaviour. The trust score is highly reliant on the number of system users. Therefore, the observed behaviour is caused by an initial steep increase in user numbers, which quickly flattens out. Most scenarios end up with a trust score between 0.9 and 1 with a few scenarios reaching the maximum trust score of 1. Regarding all observed scenarios, no significant changes are observable from tick 100 onwards.

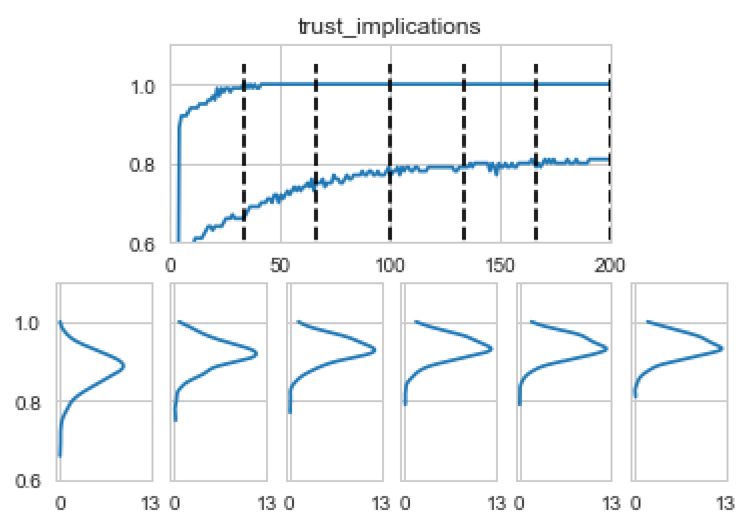


FIGURE 51 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 - TRUST SCORE

Figure 52 presents the outcomes concerning the anonymity score. An initial decrease gradually flattens out, after which the behaviour becomes linear. The KDE plots indicate that there is minimal change after tick 50 regarding the distribution of scenarios. The envelope reaches from roughly 0.5 to 0.8.

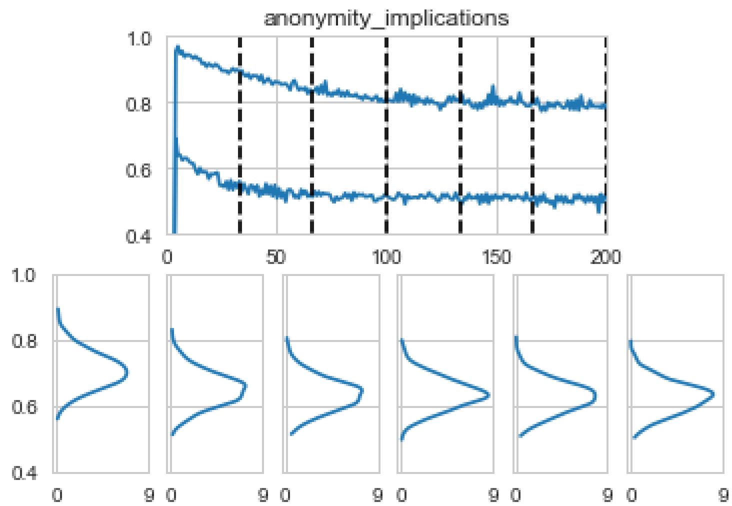


FIGURE 52 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 - ANONYMITY SCORE

Figure 53 presents the outcomes regarding the confidentiality score. After model initialisation, a number of scenarios show a sharp decrease in confidentiality score. At model initialisation, the model has no users. Therefore, a relatively large number of users start using the system. This initial surge in system users shapes the system environment. This system environment might not be beneficial in terms of effort expectancy and system performance, causing a large number of users to stop using the system. This causes the number of transactions and the total number of platform trades to decrease as well. The system needs some time to increase its performance and lower its effort expectancy. As can be seen, some scenarios better cope with this phenomenon. As user numbers start to grow, the scenarios tend to converge towards the same confidentiality score.

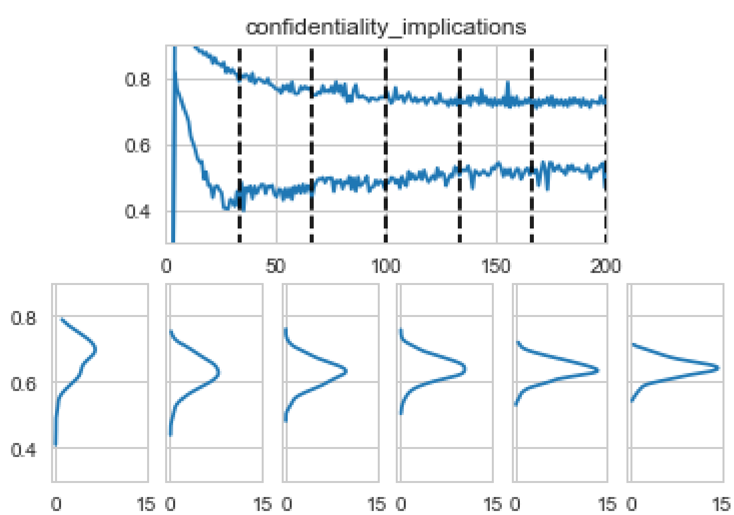


FIGURE 53 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 - CONFIDENTIALITY SCORE

6.5.3. Step 3: linking model and theory

Regarding the outcomes of the model, each design layout has its cons and pros concerning the fulfilment of ethical values. The model outcomes are concerned with the likeliness that certain ethical issues arise for the three design options. As was mentioned before, the decoupling of technology and people decreases the interpretation strength of the outcomes. Mainly because the results not portray what people actually think or what people actually value. The results should therefore not be interpreted as what will happen, but what can happen, and how likely that is. Thus, the experimental outcomes show the likeliness that ethical concerns arise related to the technological properties of the system and the dynamics imposed by the system users.

6.5.4. Step 4: comparing designs

This step portrays an overview of which ethical values are best fulfiled by each experimental design. Within this comparison, both the spread of scenario outcomes and the mean score are considered. Table 29 presents these outcomes. The results are related to the relative performance between the different experiments. The best experiment gets a "1" and the worst experiment gets a "3". When two experiments get the same score, no clear distinction between these experiments can be made solely based on the model outcomes. According to this table, no pareto optimal design can be identified.

	Privacy	*Security*	*Trust*	*Confidentiality*	*Anonymity*
Experiment 1	2	3	1	3	3
Experiment 2	1	2	3	1	1
Experiment 3	3	1	2	2	2

Table 29 Ethical value fulfilment regarding model outcomes

Considering the experimental outcomes, experiment 2 is considered the best alternative regarding privacy, confidentiality, and anonymity. The scores regarding these ethical concerns are significantly higher. However, experiment 2 tends to show lower scores for both trust and security as compared to the other experiments.

6.6. Design comparison

This section displays all outcomes to arrive at a complete comparison between the different experimental designs. Table 30 incorporates all KPIs used for model analysis. Take note that the outcomes are not as one-sided as presented.

Design layout 1 scores best on the four KPIs with respect to number of users, transactions, and traded kilometers. The constant shift between demand and supply within a centralised system induces large oscillations, which work through in the behaviour of the system. This results in high oscillations from day to day which causes shifts in the number of transactions and the number of kilometers traded on the platform. Security, confidentiality, and anonymity are least fulfiled on a centralised system. This is mainly caused due to the increased risk of hacks due to a single authority and external data storage. The fulfilment of trust is relatively high as compared to the other system designs. The large numbers of users induce trust within the community. This effect is apparently larger than the lack of trust in a single authority.

Design layout 2 scores least on the four KPIs. At model initialisation, system performance is lacking, causing a slow increase in user numbers. As the other KPIs are highly dependent on these user numbers, these KPIs logically perform less as compared to other designs. However, the strong consensus mechanism, the lack of a single authority, and the shielded distributed ledger can better fulfil privacy, anonymity, and confidentiality as values. Trust is least fulfiled as compared to the other experiments. This is caused by the underperforming consensus mechanism as a result of low numbers of users.

The experiments concerning design layout 3 show similar behaviour as compared to design layout 2. Overall, design layout 2 performs less than design layout 1 and better than design layout 3 with respect to the number of transactions, system users, and the number of traded kilometers. The fulfilment of security is high, due to the high performance of the consensus mechanism caused by higher numbers of users as compared to design layout 2. Privacy is least protected, mainly caused by a single point of authority which can freely assess privacy sensitive data of participants.

KPI	*Experimental setup*		
	Design layout 1	***Design layout 2***	***Design layout 3***
Number of users	Probably best	Probably worst	Indifferent
Number of enabled users	Probably best	Indifferent	Indifferent
Number of transactions	Probably best	Probably worst	indifferent
Number of traded kilometers	Probably best	Probably worst	Indifferent
Privacy	Indifferent	Probably best	Probably worst
Security	Probably worst	Indifferent	Probably best
Trust	Probably best	Probably worst	Indifferent
Confidentiality	Probably worst	Probably best	Indifferent
Anonymity	Probably worst	Probably best	indifferent

TABLE 30 OVERALL COMPARISON OF EXPERIMENTAL DESIGNS

6.7. Conclusions

In chapter six, the analysis of three different technological design layouts corresponding the selected experimental setup were described. Concerning the multitude of different concepts integrated in the model, an exploration study was proposed based on uncertain factors originating from UTAUT, the CA, and smart charging. The variables concerned with these concepts were validated according to what behaviour was expected with regards to the different concepts. Model analysis was split in two distinct phases. First, model robustness and dynamics were assessed concerning the variables contributing to system performance. These variables are as follows: number of users, number of transactions, number of traded kilometers, and number of enabled users.

The experimental outcomes underlined that no optimal design could be indicated based on the three designs used for experimentation. When considering a system solely implemented for high numbers of users and transactions, a centralised system pointed out to be most fit. When designing a system which should ensure the least ethical concerns on the short- and long-term, a decentralised system pointed out to be more compatible. However, these results are highly uncertain and require additional research. The EMA study showed that uncertainty highly contributes to different outcomes for each design layout.

In general the following points were concluded from experimentation:

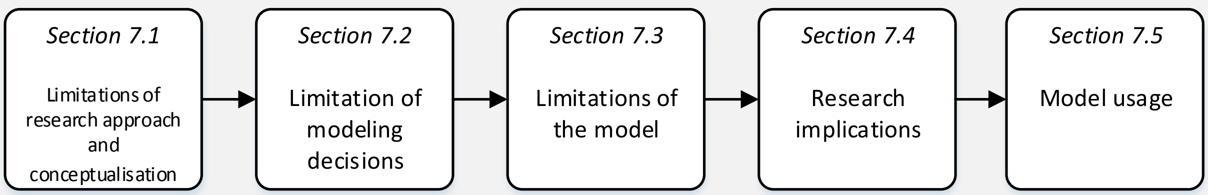
- System performance and effort-expectancy highly influence the number of users.
- Decentralised systems seem to better fulfil ethical values such as privacy, security, anonymity, and confidentiality.
- Decentralised systems with low user numbers could induce trust issues.
- Centralised systems are more unstable due to fluctuating demand and supply, causing large oscillations in KPIs related to performance.
- Centralised systems seem more prone to ethical problems on the short- and long-term.
- Centralised systems have a high initial system performance, causing a high number of system users. As such these systems score well on performance metrics such as number of transactions, and the number of traded kilometers.

7. Limitations and Implications

Structure

Before concluding this thesis, an extensive reflection on model outcomes, research approach and conceptualisation, and research implications is presented. This includes a reflection based on literature regarding the theoretical frameworks, used concepts, and the agent-based model. Limitations of the research approach, modeling decisions, and the model itself are discussed respectively in section 7.1, 7.2, and 7.3.

Several research implications have been related to literature and are elaborated on in section 7.4. In short, these implications include the relevance of the research for smart charging system design, and the potential of combining different theoretical concepts with the CA. Furthermore, for the sake of completeness, a short description on model usage is given in section 7.5.



7.1. Limitations of research approach and conceptualisation

In this section Several limitations of the research approach and conceptualisation are discussed. These limitations work through in the applicability of the conceptual model for evaluating the different smart charging designs. In order to cope with these limitations, their applicability has been reflected and elaborated on throughout this thesis. However, a complete scientific basis for application is lacking. Take note that some of these limitations are also considered contributions. These contributions are separately discussed in section 7.4.

7.1.1. Use of the Capability Approach

The CA is considered a normative framework (Robeyns, 2005). Therefore, the CA is particularly useful for making value judgements and evaluating individual well-being. However, when modeling a system, descriptive concepts are needed. Alkire (2005) states that human motivation is more extensive than presented in the CA. It includes other motivations such as for instance identity, cooperation, and sympathy. Nonetheless, in order to evaluate ethical values, the CA was used as decision making structure for EV owners.

The decision-making process within the CA is presented as non-dynamic. Accordingly, the achieved functioning of an individual, such as for instance trading electricity, has no feedback effects on the established system. Kleine (2010) indicates that the achieved functioning itself is considered the end-point of evaluation. This crosses swords with the expected reality in which trading electricity influences personal aspects like skill. This feedback has effects on further decision-making creating a dynamic setting. As the CA does not imply this type of feedback, other concepts were introduced to create dynamics.

7.1.2. Combination of explanatory concepts

Several concepts were combined in order to develop a model for smart charging. The most dominant concepts are the blockchain taxonomy of Xu et al. (2017), the unified theory of acceptance and use of technology as presented by Im, Hong, and Kang (2011), and network effects as presented by Catalini and Gans (2016). There is little to none scientific basis for including all these concepts for modeling the usage of a smart charging system. Their inclusion is solely based on the need for explanatory concepts to serve as logic for model calculations. Robeyns (2003) states that different normative results emerge, depending on which theories are added to the capability framework. The implications of these different results are two-sided. It decreases the interpretation strength of modeling results and it raises questions whether they are the only applicable concepts.

One could consider to include a variety of explanatory concepts in addition to UTAUT to broaden the exploration range. Two of these explanatory concepts could be the technology acceptance model (TAM) and theory of planned behavior (TPB) (Taylor & Todd, 1995). The inclusion of user intentions, as presented in the TAM potentially increases the predictive power of the agent-based model. TAM could provide useful as it is highly related with technology usage and system design characteristics (Taylor & Todd, 1995). Theoretical extensions of the TAM include social influence (Venkatesh & Davis, 2000). This could potentially be coupled with the social context introduced in the CA.

The theory of planned behaviour (TPB) as proposed by Ajzen (1991) could also pose a viable concept for explaining the behaviour of EV owners. TPB puts focus on the individual's intention to perform a certain behaviour. Quite similar to UTAUT, TPB reasons that accepted effort is an precursor of intention. The higher the intention the more likely the performance. Complementing the intention of performing behaviour within the TPB is the inclusion of perceived behavioral control. Some behaviours depend on non-motivational factors such as availability and resources. These factors represent the direct control people have regarding their behaviour (Ajzen, 1991). The CA acknowledges these factors as conversion factors. Therefore, using the TPB for operationalising the CA could potentially be more scientifically substantiated then using UTAUT.

7.1.3. Operationalising ethical values

Within this research, an attempt was made at operationalising ethical values. This operationalisation was needed to effectively incorporate them within the smart charging model. The consideration of ethical values for designing new technologies is considered an important aspect throughout the design process (Friedman, 1996). To incorporate the five chosen ethical values they were distanced from the actual values of people. Within the CA, ethics are incorporated by focusing on individuals. Thus the functionings and capabilities are those of an individual. It was decided that the basic capability set for each individual within the system consisted of the same 5 capabilities. The ethical values were distanced from the individual EV owners and incorporated in those 5 capabilities. Therefore, the ethical values became more tied to what the smart charging platform would enable, rather than what an individual EV owner would perceive. This shift decreased the evaluative power of the CA to determine what individual EV owners perceive as ethically acceptable or not. This limitation was earlier addressed and assessed, but remains a dominant factor.

7.2. Limitations of modeling decisions

A set of limitations regarding the modeling decisions is elaborated on. These are not necessarily problematic for the outcomes of this research, as these limitations were already translated to a wide set of uncertain parameters used for the EMA study. However, reflecting on these limitations is needed for a deeper understanding in what the outcomes mean, and which implications the research has on designing smart charging systems.

7.2.1. Validation of the model

The smart charging system is based on technological concepts rather than an existing technological platform. It is therefore harder to make an estimation of how the system should behave under normal circumstances in the real world. The different concepts implemented to operationalise the CA provide some basis for validation as these concepts prescribe how EV owners should act and react. Therefore, a large portion of model validation is based on these concepts. However, as was stated in section 7.1.3, the inclusion of the different concepts has little scientific basis. It is therefore uncertain to which extent they are valid for understanding smart charging.

An EMA study was executed in order to cope with the inability to apply strict model validation. Kwakkel and Pruyt (2013) explain that EMA can provide useful insights when limited data is available, but also when high uncertainty exists regarding which data to use. The aim was to minimise the impacts of the chosen concepts and data on the uncertainty of model outcomes. However, due to the complexity of the system and the combination of different concepts, the interpretation strength of model outcomes for real-life design decisions is limited.

7.2.2. Identification of conversion factors

It was earlier stated in this thesis that a vast number of conversion factors can contribute to the preference and other decision-making mechanisms of EV owners. A set of five conversion factors was selected, based on the assumption that this set could represent basic interaction. Sen (1993) has stated that, like capabilities, there is no definite set of conversion factors. The set of five conversion factors might lead to a too pragmatic view of the smart charging system. In dealing with this limitation, the work of Oosterlaken (2012) provided useful insights. For practical reasons, it is not expected to anticipate all capability effects of a technical artefact. Only the most relevant capabilities, conversion factors and other issues which explain the basic interaction for the design challenge need identification.

7.2.3. Limited pool of potential users

The model outcomes show the expected behaviour of KPIs related to system usage, performance, and ethical values with respect to a limited static pool of EV owners. The EMA plots for most KPIs used for data analysis flatten out. This behaviour is most likely caused by a limited pool of potential users which has a fixed number of EV owners. The scenarios used in the EMA study might display different outcomes when a higher number of users was implemented. This could have several implications for the social interaction structures, as well as the performance of the system. Furthermore, The number of deployed EVs has increased exponentially and is expected to keep increasing in the future (Lopes et al., 2011). This increase might have considerable effects on the dynamics within the system. Since the increase in EV numbers is uncertain, and equal growth for each scenario is needed for comparison reasons, the increase was not included in the model.

7.2.4. Static charging patterns

For model integration, it is assumed that charging patterns remain static. This excludes the possibility for EV owners to change their charging patterns in response to for instance changes in lifestyle, social context, and system experience. Complementing this, EV owners might seek to increase their financial gains by adopting their charging patterns. Within the neoclassical model of consumer behaviour this search for increased financial gains is referred to as: constrained maximisation of profits (Van den Bergh, Ferrer-i-Carbonell, & Munda, 2000). A form of profit maximisation is presumably present within a smart charging system. The effects of profit maximisation are not explored by the model. Its effect is therefore uncertain. However a change of charging patterns consequently results in a change in the systems performance according to the concept of performance expectancy. Performance expectancy increases or decreases depending on the mean charging pattern of all system users. The effects of profit maximisation by EV owners could therefore be widespread.

7.2.5. Relativity of time

Within the agent-based model, time has a relative function. With regards to the charging behaviour of EV owners, a time step within the model represents a day. Within this day, EV owners drive their daily driving distance, determine whether they want to sell or buy electricity, and store their EV accordingly. For the other concepts within the model, such as the increase of skill, a time step in the model cannot be directly related to the actual increase of skill due to the uncertainty of daily skill increase. The increase of skill is chosen in accordance to the model run time, such that the increase of skill develops according to the presented concepts. The time steps used to represent the behaviour of the different KPIs cannot be translated to actual time steps in the real world. This results in three uncertainties related to time: it is uncertain (1) how long it will take till behaviour takes place, (2) how long an increase or decrease will take, and (3) at which point in time a maximum or minimum is met.

7.2.6. Performance versus potential profits

The term *performance* relates to the efficiency of the smart charging platform. To this extent, it relates to the factors contributing to factors important for a potential system facilitator. The factors contributing to performance were identified as the number of users, the number of transactions, and the number of traded kilometers. Take note that these performance metrics do not inherit any form of costs or profit. It is highly likely that the different designs have different fixed and variable costs. These have not been evaluated within this thesis and require further research. Nonetheless, the model outcomes give an indication to which design is expected to perform better regarding factors which likely have a large effect on potential monetary profits. These results are useful in further assessing the financial impacts of the smart charging system. This does however require to identify the costs of system implementation, and the costs of maintaining the system.

7.2.7. Design decisions

The four architectural design decisions as presented by Xu et al. (2017) were used within this thesis. The actual design and implementation of a smart charging platform is expected to be far more extensive than these four design decisions. The other decisions are expected to further impact the performance of the system and the impact on ethical values of system users. The limitation of design decisions is not necessarily problematic for interpreting the model outcomes. The design taxonomy of Xu et al. (2017) is particularly useful for exploring the conceptual design space. Furthermore the taxonomy enables the comparison and assessment of various design options. Which is exactly what this research was intended for.

7.3. Limitations of the model

No model is complete or perfect simply because of the vast complexity of even the smallest interaction. A limited list of model interaction which has not been implemented in the agent-based model is elaborated on. Within this research, focus is placed on aspects typical for CA and CAS related research. These aspects are therefore logically redirected from the data that is needed to create a model. The lack of completeness isn't necessarily a bad thing. Agent-based models do not entail believability, but are rather purposefully restricted to the very few properties that matter. Or as Helbing (2012) phrases: *"they should be in reasonable agreement with later empirical observations or experimental results"*. three limitations, or rather, the purposefully neglected factors are described.

7.3.1. Hourly charge and discharge time

In a real world scenario, different EV owners would travel at different time. Therefore, they would be connected to the grid at different times. These individual traveling patterns are expected to have an effect on the performance of the system. The agent-based model was not intended to simulate a real world scenario in which the optimal setting of a platform could be predicted. The model was intended to enable the assessment of relative performance between system layouts with respect to number of users, transactions, and at which point in time these users start or stop using the system based on whether they fit within the system environment. As much as different travelling times could add realism to electricity trade, the process of trading electricity is not a core component of this research.

7.3.2. Electricity prices to enable competition and strategic behaviour

The transactions within the conceptualised system are based on a static price. In other words, all transactions are equally priced. This leaves little space for competitive behaviour and price optimization. In a real life situation, when demand and supply change, prices tend to change as well. This creates incentives to change driving behaviour and to maximize financial profits. Which is one of the main positive effects when aiming to level out electricity demand during the day. This was intentionally left out since the model is supposed to identify which EV owners will use the system based on the system performance rather than financial gains. Modeling the mix and match algorithm including financial incentives and profit maximisation would add value in terms of understanding financial motives and the effects on driving behaviour. For the model it was decided to include driving distance and charging patterns solely for determining the system performance for an individual EV owner.

7.3.3. Partially charged EVs and state of charge (SOC)

The conceptualised model assumes that when a system user aims to charge its EV, it will fully charge the batteries. Consequently, EV owners buy too much electricity from the grid. In theory, EV owners only have to charge upwards to the level that they can travel their daily driving distance and their batteries charge remain at an acceptable level. For this behaviour, no theoretical foundation was found. It was therefore decided not to implement this behaviour. The concept could however increase the performance of the system as it leaves more room for strategic charging behaviour. An important factor in determining how fast an EV battery can be charged is the state of charge of the EV. In normal practice, de-linearisation of charging process occurs when the battery charge level gets closer to 100%.

7.4. Research implications

The research outcomes have several implications which need further elaboration. Four main implications of this research have been selected, namely: (1) the implications for designing smart charging platforms, (2) the relevance of ABM for technology design incorporating ethical values, (3) the potential of combining the capability approach and the unified theory of acceptance and use of technology, and (4) the potential of combining the capability approach with agent-based modeling.

7.4.1. Implications for designing smart charging platforms

According to the model outcomes, designing a smart charging system shouldn't be solely focused on either performance metrics or ethical values of users. Doing so, could potentially result in a system that underperforms or a system that is prone to ethical concerns by users. Taking a user oriented view in conceptualising a smart charging system has underlined that when designing a smart charging system, a combination of both centralised and decentralised system components could suffice.

Scientific relevance

It is expected that, due to the increase of electric vehicles, EV charging management systems are needed to cope with the peak time EV charging habits of consumers (Abousleiman & Scholer, 2015; Chung, Chu, & Gadh, 2013). The habits of people have significant implications for the power system and, if not properly designed for, could cause power losses and voltage variations (Abousleiman & Scholer, 2015). The design of a smart charging system, as proposed in this thesis, aims at balancing the different habits of people regarding charging patterns. Previous examples of smart energy technologies such as smart meters pointed out that ethical concerns pose significant barriers for system integration (Cavoukian et al., 2010). Therefore, the design of smart charging systems should focus on fulfiling the ethical values of potential users as well. This research proposes a research approach which incorporates the core aspects crucial in designing smart charging systems. The research outcomes show that ethical concerns likely exist concerning a smart charging platform, and that the extent of these concerns can change over time. This underlines that these concerns should be taken into account when designing a smart charging system. The use of the CA and UTAUT provided a framework for assessing these concerns, whilst keeping focus on both the decision-making of EV owners and the performance of the technology.

Concerning this approach it became clear that both centralised and decentralised aspects prove useful in designing smart charging platforms. Therefore, when designing smart charging systems, a combination of both centralised and decentralised aspects should not be overlooked. Furthermore, the notion that decentralised platforms, for instance based on blockchain technology, perform better then single authority centralised systems is not necessarily true. Complementing this, studies focusing solely on technology performance might overlook the possible ethical concerns that possibly arise in the future. Therefore, these high performance systems could be less used than originally anticipated based on study results.

7.4.2. Relevance of ABM for technology design incorporating ethical values

Agent-based modeling was used to evaluate the fulfilment of ethical values over time. It assumes that ethical values of a person are not restricted, but can change over time according to personal changes and changes in the environment. To this extent ABM helps to understand the development of technologies with respect to the ethical concerns that these technologies might undergo. The approach is fundamentally different compared to for instance, value sensitive design. Value sensitive design is an approach to technology design accounting for human values throughout the design process (Friedman, Kahn, & Borning, 2002). The approach taken within this research is more focused on the possible concerns that arise due to the dynamics of the system. The approach assumes that the values of users are not static but change over time due to changes in the system and the social environment

Scientific relevance

In a large number of social sciences, conducting experiments is either impossible or undesirable (Gilbert, 2008). This is mainly caused due to the inability to view social systems in isolation. When considering real-world human interaction, ethical considerations and other contextual factors are at play (Janssen & Ostrom, 2006). Furthermore, concerning social dilemmas, the model of the *economic* man (which is solely searching for economic gains) can no longer explain behaviour outside of open competitive situations. Scholars should no longer presume that people only seek short-term, material benefits (Janssen & Ostrom, 2006). The use of an agent-based model within this thesis provides an alternative for conceptualising ethical values, and link them to the functioning of a system. As such, changes in the system and system environment work through in the fulfilment of ethical values, creating an image of value fulfilment beyond the short-term. This doesn't necessarily mean that the approach is ethically justified. It does mean that the chosen approach further enables the use of agent-based models for experimentation in social sciences with respect to the inclusion of ethical values of people in a demarcated system.

7.4.3. Potential of combining CA and UTAUT

In order to operationalise the CA, UTAUT was introduced. Four key constructs are used to supplement the normative framework of the CA. UTAUT is in particular considered applicable as the four constructs consist of both technology performance related factors as well as social/network factors. Effort expectancy and performance expectancy are highly related to the overall performance of the system. The link to the CA is made by including the effects of system performance within an overarching social structure including a social influence. This link is considered justified as the CA explicitly mentions a social context which incorporates both elements related to the system as well as social influence from other users. Perhaps most importantly, UTAUT identifies a method of quantifying the preference mechanisms of persons. This is particularly useful for creating agent-based models of a system, as decision-making mechanisms can then be based on quantified values and calculations. To this extent, the inclusion of UTAUT offers a method of creating agent-based models of model concepts derived from the CA.

Scientific relevance

The inclusion of UTAUT within the CA has several scientific implications. To accommodate the extension of the CA it is important to note that Sen always aimed at enabling the extension of his approach by combining it with other theoretical approaches (Kleine, 2010). Within the work of Robeyns (2005) it is hinted that the integration of other evaluative methods are needed in order to arive at a deeper understanding of the CA. The constructed conceptual model combining the CA and UTAUT is useful for evaluating the effects of a particular complex system on the well-being of people and their social arrangements. This provides an answer to the problem of including quantified social relations, which was a main point of critique of the current CA (Robeyns, 2003). The complexity of the system is encapsulated and represented by four constructs. This creates a form of mainstay in the indefinite normative framework of the capability approach. This mainstay is particularly useful to determine individual decision-making, for which the CA is a less prevalent approach in general (Robeyns, 2011).

7.4.4. Potential of combining CA and ABM

The mentioning of heterogeneity, individual decision-making, and interaction in both the CA and ABM was considered as a justification to combine the approaches. Although both research approaches share a large overlap in concepts, an extension of the CA was needed. Most importantly, a form of dynamics was added to the CA approach. This was done by taking away the formal end-point of analysis within the CA. Originally, this end-point was considered the achieved functioning of a person. A relation between the achieved functioning with the larger social context as well as the conversion factors of a person was included. By doing so, the actions of a person have a direct or indirect effect on other persons in the system environment. This further enables the CA to be used for the analysis of complex adaptive systems.

Scientific relevance

Sen (1993) and Robeyns (2005) hinted towards the integration of other theoretical approaches within the CA. Scholars have raised doubt whether the framework is effectively operationalisable (Chiappero-Martinetti, Egdell, Hollywood, & McQuaid, 2015). According to Chiappero-Martinetti et al. (2015), operationalisation is defined as: *"the diverse sequence of transforming a theory into an object of practical value"*. The authors specifically mention two steps to achieve this. Firstly, the theory has to be quantified. Secondly, the theory should be put to use. In contrast to UTAUT, which was used as a quantification method, ABM provides the tools to actually analyse the proposed problem. The experiences with operationalising the CA are in line with the expectations Sen (1993) already argued for. First, The CA can only be adequately used when it is combined with other theories to fulfil the usability criterion. Furthermore, the combination of different theories causes restrictions. These restrictions most notably worked through in the interpretation power regarding the different ethical concerns.

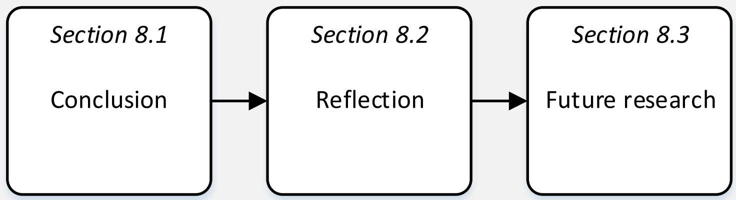
Robeyns (2005) and Sen (1993) did not provide clear guidelines as to how the CA could be operationalised. This thesis provided insights regarding these guidelines when aiming at an agent-based modeling study combined with the conceptual framework of the CA. A first step should be to indicate which parts of the CA are actually useful in analysing the proposed problem. These parts of the CA can then be conceptualised with respect to the system environment. Before quantifying the conceptual model, it should become clear which relations and components in the CA are missing to create an agent-based model. In doing so, it should become clear which data is needed, and which theory is applicable for quantification.

7.5. Model usage

The model in itself can be used to further explore different technological designs. Within this thesis three different types of designs are assessed. The model in its current state allows for 78 more designs to be explored. The developed model allows for incorporating different model extensions. The variables needed to calculate effort- or performance-expectancy are established in separate functions. Therefore implementing an expansion of the concepts related to UTAUT is relatively easy. When using the model, the limitations as presented within this chapter should be considered. The model in its current state cannot be used for direct interpretation for real world decisions. It is rather a tool for exploring different designs and their possible outcomes. The outcomes can then be used to select promising technological designs. These designs can then be further explored.

8. Conclusions and reflection

Structure
This chapter summarises the main findings with regard to the research questions. A brief answer is formulated for each of the research questions based on what was concluded in this research. In extent a reflection on the model, the research approach, and the research process is presented. This reflection is supplemented with a short elaboration on the impact of this research in light of the energy transition. In conclusion, Directions for future research are presented.



8.1. Conclusion

1. ***Which technological design options exist when designing a smart charging platform, and which ethical concerns arise when these design options are implemented?***

In answering this research question, the research of Xu et al. (2017) was used as guideline. When designing a smart charging system, four architectural design options are considered: (1) Level of decentralisation, (2) data storage method, (3) Blockchain configuration, and (4) consensus algorithm. Xu et al. (2017) describe these architectural design options as the key components in constructing any blockchain based transaction system. For each of the four design options, three alternatives are considered. Therefore, a total of 81 unique designs can be assessed. Five ethical values were linked to the technological layout of the smart charging system: Privacy, security, trust, confidentiality, and anonymity. For modeling purposes this list was not further complimented.

2. **Which individual personality factors contribute most to the differences between individual EV owners?**

In compliance to the capability approach, personality factors are considered similar to conversion factors. Sen (1993) argues that, for the analysis of a system, the number of conversion factors should be limited to the those needed for the research goal. For a smart charging system, five conversion factors were chosen which describe the possibilities and basic actions of EV owners. These conversion factors are:

- *Skill*: The overall skill level of an EV owner with respect to using the smart charging system. The higher the skill, the less effort is needed to use the system and the more added-value is achieved from using the system. Skill increases when the system is used.
- *Intelligence*: The overall intelligence level of an EV owner. Intelligence contributes to the learning process of using a technology. Therefore, the intelligence level determines the level of skill attainment as well as the performance of the system.

- *charging patterns*: Indicate the level of charge at which an EV owner is willing to charge its EV. Higher level charging patterns indicate EV owners which usually charge their EV at each possible instance. Lower level charging patterns indicate EV owners which usually charge their EV whenever a low charge threshold is met.
- *daily driving distance*: The quantity of kilometers an EV owner drives on a daily basis.
- *battery range*: The total number of kilometers the EV of an EV owner can drive with a fully charged battery.

It is likely that more conversion factors contribute to the behaviour of EV owners. The five that were selected describe the basic interaction needed in order to analyse the chosen KPIs. During the analysis of the conversion factors it was found that these factors were influenced through the dynamic interaction among EV owners within the system environment. Several concepts were introduced to explain this interaction. The most dominant concepts are effort-expectancy, performance-expectancy, and social influence originating from UTAUT as proposed by Venkatesh et al. (2012). These concepts were used to operationalise the capability approach, which enabled model development.

3. **How can a model be developed, that gives insights in the short- and long-term effects of different design options regarding the fulfilment of ethical concerns and technology-usage?**

In order to develop a model, several concepts had to be quantified. The quantified technological, social, and ethical concepts were linked to establish a quantified conceptual model. The decision-making logic central in the CA was used to describe the actions and interactions of EV owners in the system. Technology usage is related to the factors contributing to the decision-making of individual EV owners. Effort-expectancy, performance-expactancy, and the social context needed quantification. It was argumented for that effort-expectancy highly relies on the practical experience of a user, the required-skill for system operation, and the flexibility of the proposed system. Performance-expectancy was assumed to rely on the system performance, the number of users already using the system, electricity supply and demand, and the charging patterns of other users.

A clear distinction between ethical concerns and technology-usage is implied. The ethical concerns were quantified by decoupling the values of EV owner from the value fulfilment of the system. Within the CA theory, people value a certain action more than they value another. This value judgement is person specific. Therefore, these values would have to be integrated within the agent-based model as agent states. This was found impractical for several reasons, including the inability to properly distribute ethical values of people. In order to retain focus on ethical values, these values were placed upon actually using the system. As such, the model outcomes indicate the ability of the system to cope with ethical values with respect to the technology. The outcomes can not be directly translated to the risk of ethical problems arising, or the risk of people leaving the system. They do however show which system is likely better fit to deal with ethical concerns.

4. **What can be concluded when comparing different design options?**

Centralised systems have a high initial system performance. This causes high numbers of EV owners to start using the system. High usage numbers induce steep skill increase levels which further accelerate the performance increase of the system. Overall, these systems achieve high performance levels with respect to number of transactions and number of traded kilometers. However, centralised systems are considered more unstable as compared to decentralised systems. Fluctuating demand and supply cause large oscillations in the number of transactions and the number of traded kilometers. These oscillations could potentially be a problem as the system needs to be able to deal with these. Centralised systems are considered more prone to ethical concerns. Specifically anonymity is considered problematic, as the model outcomes present extremely low scores for this value. To this extent, people who value anonymity will potentially not use a centralised smart charging system.

Decentralised systems generally have less users, less transactions, and less traded kilometers as compared to centralised systems. In addition, when these systems have very low user numbers, trust issues arise. On the other hand, values such as privacy, security, anonymity, and confidentiality are fulfiled to a higher extent as compared to a centralised system. The consensus mechanisms of a decentralised smart charging platform can better shield against infringement on these values. Furthermore, the lack of a single authority, creates an environment in which these values are better fulfiled.

5. **How can a smart charging system be designed which is both used on the short- and long-term and fulfils ethical values of EV owners?**

A smart charging system that is used on the short- and long-term and fulfils the chosen ethical values, can be designed by combining centralised and decentralised design elements. The exact combination of design elements is at this time still uncertain. The combined theoretical framework gives way for extended research in combined system designs with the possibility for system optimisation. A centralised platform looks most promising concerning performance indicators such as number of users and number of transactions. It is important to further identify, which centralised system components highly increase these KPIs. These system components can be combined with decentralised system components in order to create a secure trustless environment in which privacy and anonymity are safeguarded. Such a system appears to have contradicting elements, as a system containing centralised components always exerts some sort of power to a single or multiple authorities. The experiment outcomes pointed out that this power exertion is not necessarily a bad thing. The research clearly indicates that further research in a combined system is justified.

The research has several implications for designing smart EV charging systems. First of all, the research has shown that when incorporating ethical values within the assessment of technologies, the CA is a proper method for conceptualisation. The CA allows for the creation of agent-based models. Furthermore, different theories, such as UTAUT, can be combined with the CA to add meaning to the different relations within the CA. Using this approach to design smart charging systems helps to keep focus on the actual well-being of persons, rather than solely focusing on technological performance. In addition to for instance the theory of planned behaviour, the approach in this thesis, adds a longer term perspective. This is particularly useful in assessing different design alternatives regarding long-term performance metrics.

8.2. Reflection

This section personally reflects on different aspects within this thesis. The main function of this section is to personally elaborate on the model, the process, and the research approach with the main goal to learn from these experiences. Others may find these experiences useful when executing their own projects on similar or completely different topics. Furthermore, a personal reflection on the implications of this research regarding the energy transition is presented.

8.2.1. Reflection on the model

In all honesty, I did not anticipate the agent-based model to look anything like it does at this point. The model includes a set of combined concepts which I identified during model development. This was mainly due to the need for an explanatory concept related to the performance of the smart charging system. Due to the inclusion of different concepts, the model behaviour is largely dependent on these concepts, rather than the emergence of EV owner interaction. However, the extent of the behaviour and the tipping points were caused by the interactions of EV owners with the platform and the indirect interactions among EV owners.

The most useful property of the model is, in my opinion, the ease of extending it. The way the code was written allows for changes and extensions of platform components, conversion factors of EV owners, and a wide range of concept variables. These future extensions were considered during model development mainly because I knew the model wasn't going to be applicable to a wide range of systems. In my view the model should have a core functionality applicable to many fields, and an upper layer of technology specific elements which could be easily altered. As such, whole new concepts can be introduced by simply altering the calculations for performance and effort. This does however require that the conceptualisation of UTAUT remains implemented.

Reflecting on the limitations of the model presented in section 7.3, I think that the inclusion of electricity prices and hourly charge and discharge times would significantly increase the dynamics of the smart charging system. Dynamic electricity prices should serve as a strong incentive for customers to perhaps change their charging patterns. The smart charging platform could use these incentives to steer charging patterns and cause slight alterations in the charging patterns of EV owners. This could perhaps result in higher system performance, albeit this has not been explored by the system. Hourly charge and discharge times would add a significant realism factor to the model. They could also provide a basis for exploring the effectiveness of smart charging for demand response.

8.2.2. Reflection on the process

Arriving at a problem statement and elaborating on applicable research approaches and methods was to my experience a rather iterative process. Due to the my lack of knowledge on smart charging systems and protocols I found myself rewriting several parts of the problem formulation. Exploring literature regarding a comparable technology, such as smart metering services, helped me come to grips with how to identify my own research problem. Since the capability approach prescribes different components needed in order to evaluate the well-being of a person, the search for data was rather structured. The primary focus was to identify conversion factors, technology components, and explanatory concepts to fill the gaps within the normative framework of the capability approach. In my experience it is not easy to combine different theoretical concepts let alone argue for the applicability of the combined whole. I considered this part of writing my thesis as the most challenging. The use of the concepts acceptance, adoption, and technology usage is, in my experience, highly intertwined and the terms are used in various settings under various assumptions.

8.2.3. Reflection on research approach

Learning about the capability approach made me aware of just how applicable a normative framework for the evaluation of broad terms as well-being is for assessing technology performance. The capability approach provided a great tool for conceptualising model behaviour, mostly because the logic of the capability approach can be demarcated in different consecutive steps. Reflecting on the research approach made me aware of the enormous number of possible assessment methods in existence. The scope and research approach applied in this thesis is just one of many scopes and approaches applicable. This generates mixed feelings. On the one hand the model outcomes could have limited impact on actually solving the problem introduced in this thesis. On the other hand, this research is one of many steps towards unlocking the true potential of electric vehicles. I hope that more people are willing to further explore the possibilities and effects of smart EV charging systems.

8.2.4. The bigger picture

This section presents a brief reflection on the overarching topics fundamental to this thesis. These topics include the energy transition, the introduction of blockchain systems, and the design of smart energy technologies.

The energy transition

The storage potential of EVs and the need for smart charging protocols to enable this storage potential was the starting point of this thesis. This thesis pointed out the potential of combining decentralised and centralised system components in fulfiling ethical values of users. The role of energy storage through EVs should be nuanced for 2 distinct reasons: (1) the actual storage potential at this point in time is relatively small, and (2) there are more methods to cope with the intermittency of renewable energy sources.

The energy outlook provided a clear trend in sold EVs throughout Europe. If the current trend continues, it is expected that in time, large numbers of EVs will roam around. It is at this stage that the real potential of EV electricity storage and V2G integration is unlocked. However, it remains uncertain how the introduction of EVs will develop due to uncertainty in policies, technological advancements, and perhaps the introduction of alternative transportation methods.

Energy storage is one of many methods to cope with the increased intermittency of renewable electricity sources. Demand response, lowering energy usage, and integrating renewable energy sources with a constant output are potential solutions as well. With respect to these solutions, I believe that a combination of these measures is more likely to succeed. Energy storage can definitely contribute in achieving a stable electricity supply within a world in which electricity is largely generated by intermittent energy sources. However, Storage itself should, in my view, not be considered as the main solitary solution.

Blockchain integration

Blockchain based systems are commonly defined as trustless environments in which privacy and anonymity can be adequately safeguarded. This thesis pointed out that ethical implications are indeed expected to be less likely as compared to centralised systems. However, the notion of trustless environments doesn't fully hold within a smart charging setting. A more nuanced stance should be taken when deciding on implementing blockchain platforms. One should not simply state that trust won't be an issue due to the trustless environment.

Furthermore, it is commonly stated throughout media that blockchain technologies have no single point of authority. One should consider whether this is actually wishful. An intermediary might be completely justified in a setting in which some form of power is needed to manage and whitelist participants. The proposed system within this thesis is concerned with, in my view, a critical part of our daily lives. Therefore, a trusted intermediary, as for instance the government, could be used to manage, alter, and operate a smart charging system. This thesis pointed out that such a centralised instance positively affects the performance of the system. When considering a centralised system, it is important to understand which parts of a distributed ledger are needed in order to operate such a system. When these parts can easily be replaced by *common* centralised components, whilst safeguarding ethical values, one should consider not to implement blockchain technology at all.

Smart energy technologies

It is expected that the role of fossil fuels will lessen. Subsequently the role of wind, solar, and biomass are expected to increase. Due to the high intermittency of wind and solar, the ongoing energy transition towards a sustainable society requires the integration of integrated energy systems (Lund, 2007). Conventional fossil-fuel based systems highly influence energy investments. The introduction of new energy technologies, such as a smart charging systems, should be assessed on a longer timescale. Therefore, I believe that research in these topics should not be delayed till enough electric vehicles are available. There is one learned lesson in particular regarding this thesis. Exploratory research is possible and useful, no matter how little information one has.

8.3. Future research

This section presents several directions for future research. Six future research directions are elaborated on. All research directions should lead towards a more concise answer to which smart charging design is to be implemented.

- Focus on one particular design

To explore a larger set of scenarios, three design layouts were considered for experimentation. EMA provided a useful approach for analysing the robustness of designs. One could consider to explore a certain technology design in depth by increasing the number of scenarios for one particular design. Considering the outcomes of this thesis, a centralised system could be further explored in order to identify design decisions which better comprehend with future ethical concerns. By doing so, a more focused research approach and literature study could provide better insights in the performance of a centralised system.

- Focus on all possible designs

The range of design alternatives holds 81 unique designs. One could consider adding all the designs as exploration variables to a new EMA study. By doing so one could potentially identify which design direction is most promising regarding the chosen KPIs.

- Extending the scope of design alternatives

The work of Xu et al. (2017) was used as a descriptive taxonomy. However, developing smart charging contracts is considered much more complex. One could explore the effectiveness of different smart charging contracts and how people deal with the complexity of these contracts. Complementing this, legal accountability should be explored as real world assets are at stake.

- Assess need for large-scale EV storage

One of the starting points for this thesis was the assumption that smart charging protocols are needed to (1) cope with the increased load on the electricity network and (2) to unlock the potential of electric vehicles as storage devices. In order to justify the need for unlocking the storage potential, further research on the impact of using these vehicles as storage is perhaps needed. This can further nuance the storage potential of EVs.

- Further explore the integrated approach of CA and CAS

A first attempt at operationalising the CA with the inclusion of CAS was made. This attempt needs to be further worked out to identify possible implications and possibilities of the integrated framework. In addition to this thesis, a paper was written on the integration and applicability of the CA and CAS. This paper can be used to further explore the applicability of this integrated framework.

- Quantify the smart charging model

The model used within this thesis is far from complete, one could consider to include hourly charge and discharge times, electricity prices, and different charging durations based on charging levels. This results in a more dynamic model which is assumed to be less easily optimised, and therefore hold different insights. Take note that this does require the identification of new conversion factors as well.

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Appendices

Appendix A: Agent, environment and object states formalisation

Appendix A presents an overview of the states of the agents used in the agent-based model. Furthermore, the states of the system environment and objects are defined. For each state presented in appendix A, a short description is added. Table 31 elaborates on the states of EV owners. Table 32 describes the internal states of the smart charging system. Table 33 presents an overview of the global states of the model.

Agent	*States*	*Description*
EV owner	Skill	The amount of skill this agent has represented between zero and one.
	Intelligence	The amount of intelligence this agent has represented between zero and one.
	Charging-pattern	The minimum amount of EV-charge this agent deems acceptable before charging its EV.
	Daily-driving-distance	The daily driving distance of an agent driven in kilometers.
	Battery-range	The total number of kilometers the EV of this agent can drive on a fully charged battery.
	Effort-expectancy	The expected effort of this agent regarding the technological layout of the smart charging system.
	Performance-expectancy	The expected performance of the system regarding the specifics of the agent and the technological layout.
	Social-influence	The value of social influence on this agent.
	Uses-system?	Whether this agent is using the system or not.
	System-usage-counter	How many days this agent has used the system.
	Can-use-system?	Whether this agent is enabled to use the system or not.
	EV-charge	The current charge of the EV of this agent presented between zero and one.
	Wants-to-charge?	Whether this agent is aiming to charge its EV.
	Wants-to-sell?	Whether this agent is willing wo sell electricity that is stored in its EV.
	Bought-from-grid	How many kilometers of EV charge this agent has bought from the grid
	Bought-from-platform	How many kilometers of EV charge this agents has bought from the platform
	Bought-from-platform-this-tick	How many kilometers of EV charge this agent has bought from the platform this day.
	Number-of-platform-trades	How many electricity transactions this agent has executed on the platform
	My-peers-this-tick	How many other EV owners this agent has traded electricity with this day.
	I-switched	Indicator of how many times the EV owner has switched from using the platform to not using the platform and vice versa.

TABLE 31 DESCRIPTION OF AGENT STATES

Agent	States	Description
Smart charging platform	Fundamental-properties	The fundamental properties of the system layout based on the taxonomy of Xu et al. (2017).
	Anonymity-score	The score of anonymity fulfilment of this system over time.
	Privacy-score	The score of privacy fulfilment of this system over time.
	Security-score	The score of security fulfilment of this system over time.
	Confidentiality-score	The score of confidentiality fulfilment of this system over time.
	Trust-score	The score of trust fulfilment of this system over time.
	Required-skill	The required-skill of EV owners to participate within this particular system layout.
	System-performance	The initial system performance of the system based on the taxonomy of Xu et al. (2017).
	System-flexibility	The degree of flexibility this system has to changes in the system environment with respect to increase of transactions and users based on the taxonomy of Xu et al. (2017).

Table 32 Description of smart charging platform states

Agent	States	Description
Globals	Social-influence-value	The global system influence independent from agent specifics.
	System-demand	The total demand of electricity (represented in kilometers) of all system users.
	System-supply	The total supply of electricity (represented in kilometers) of all system users.
	EVowners-willing-to-buy	The sum of system users which are willing to buy electricity.
	EVowners-willing-to-sell	The sum of system users which are willing to sell electricity.
	Total-number-of-peers	The sum of the number of peers of system users.
	Transactions-this-tick	The total number of transactions executed on this day.
	Bought-from-platform-this-tick-global	The total number of kilometers sold through the platform on this day.
	Privacy_implications	Indicates the total privacy score of the platform at this tick
	Trust_implications	Indicates the total trust score of the platform at this tick
	Security_implications	Indicates the total security score of the platform at this tick
	Confidentiality_implications	Indicates the total confidentiality score of the platform at this tick
	Anonymity_implications	Indicates the total anonymity score of the platform at this tick
	Profitability_transactions	Indicates the profitability regarding the total number of system transactions at this tick
	Profitability_traded_kilometers	Indicates the profitability regarding the total quantity of traded kilometers at this tick
	Total_amount_of_users	Indicates the total number of users at this tick
	Amount_of_enabled_users	Indicates the total number of enabled users at this tick
	Mean_skill_of_users	The mean skill of all system users
	Mean_charging_pattern_of_system	The mean charging pattern of all system users
	Mean_social_influence_of_EVowners	The mean social influence of EV owners
	Mean_peers_per_user	The mean number of peers a system user has
	Grid_vs_platform	Fraction of electricity bought from the grid as compared to the platform.
	Social_influence_value	Social influence value of the platform
	Mean_system_usage_time	Mean time an EV owner has used the system (in ticks)
	Amount_of_switches	Total number of switches of EV owners

TABLE 33 DESCRIPTION OF GLOBAL MODEL VARIABLES

Appendix B: Model initialisation

Aside from all model functions and concepts executed during the model run, it is important to initiate a setup as starting point for the model run. The model user should have as much power needed to make the necessary decisions regarding model setup. Due to the complexity and extensiveness of the model, not each model parameter should be alterable. This would result in a too convoluted user interface.

Appendix B.1 Model setup procedures

Three model setup procedures are executed in order. They mainly focus on initiating the agents in the model and shaping the initial social context of the system. These procedures are: (1) establishing the EV owners, (2) establishing the smart charging platform, and (3) establishing the social influence.

(1) The key functions of establishing the EV owners within the model are as follows:

- Set skill of EV owners equal to the minimum-skill that is selected in the UI supplemented by a random-float variable with a maximum of one. By doing so the skill of an agent lies between the minimum-skill and one and is randomly distributed among agents
- Set intelligence of EV owners equal to a random number between zero and the intelligence distribution chosen in the UI.
- Set the EV charge of an EV owner equal to a random-float number between zero and one.
- Set the charging pattern of EV owners equal to a random-normal distribution equal to the charging-pattern-spread chosen in the UI with a standard deviation of 0.1.
- Set the daily driving distance of an EV owner equal to the daily driving distance distribution. In doing so the daily driving distance of an EV owner lies between 0 and 200 kilometers a day.

(2) The key functions of establishing the platform within the model are as follows:

- Create initial values for the different platform specifics; privacy-score, security-score, trust-score, confidentiality-score, anonymity-score, required-skill, system-performance, and system-flexibility
- Give values to these scores based on the technological layout specified in the UI.

(3) The key functions of establishing the social influence within the model are as follows:

- Create a local value for the number of agents that are using the system
- Create a local value for the number of agents that are not using the system
- Create a local value for the fraction of agents using the system as compared to total agents within the system
- Create a local value for the mean skill of system users
- Set the social influence value equal to the mean skill of the system users multiplied by the social networking effects.

Appendix B.2 User interface

The user interface contains all elements, were it procedural or initialisation wise, which the model user can alter. Table 34 presents an overview of the different UI elements and their respective decision levels.

UI element	*Levels*
Level-of-decentralisation	(1) Decentralised (2) Semi-decentralised (3) Centralised
Data-storage-method	(1) On-chain smart contracts (2) On-chain log events (3) Off-chain data storage
Blockchain-configuration	(1) Public (2) Consortium (3) Private
Consensus-protocol	(1) Proof-of-work (2) Proof-of-stake (3) Byzantine-fault-tolerance
Number-of-EV-owners	[0 – 1000 , 1]
Charging-pattern-spread	[0 – 1 , 0.1]
Minimum-skill	[0 – 1 , 0.01]
Battery-range-spread	[20 – 100, 10]
Intelligence-distribution	[0 – 1, 0.01]
Performance-threshold	[0 – 1, 0.01]
Effort-threshold	[-1 – 1, 0.01]
Exp-network-effects	[0 – 5, 1]
Skill-de-linearisation-value	[0 – 1 , 0.1]
User-absence compensation	[0 – 1 , 0.1]
Min-skill-att-value	[0 – 1 , 0.01]
Comparison-supply-PCP	[0 – 1 , 0.1]

TABLE 34 OVERVIEW OF UI ELEMENTS AND DECISION LEVELS

Appendix C: Model verification

For model validation, three verification steps were executed; (1) single-agent verification, (2) interaction testing in a minimal model, and (3) multi-agent verification. The sub-appendices within appendix C are concerned with describing these verification steps.

Appendix C.1: Single-agent verification

Within single-agent verification, the behaviour of each type of agent within the system is verified. First, sanity checks are executed to monitor the agent behaviour under normal operating inputs, with the aim to identify deviations from the theoretical predictions which form the foundations of the agent's behaviour. When such a deviation is identified, it has to be resolved. Furthermore, it is tested whether the agent will break or perform unintended actions when unrealistic parameters are initialised. When this is the case, further verification is required to identify whether the model can generate these values on its own. Lastly, a set of extreme parameter values is implemented to identify whether agents respond logically to these extremes.

Appendix C.1.1: Sanity checks EV owner initialisation

- When a minimal *skill* value of 0.5 is initiated, an EV owner can never obtain a skill value lower than the initiated 0.5 during the entirety of the model run.

  Confirmed

- The *battery-range* of an EV owner cannot exceed a minimum of 150 and a maximum of 325. The actual value is normally distributed between both limits.

  Confirmed

- The *charging-pattern* of an EV owner cannot exceed a minimum of 0 and a maximum of 1. The actual value is normally distributed between both limits, depending on the changeable charging-pattern-spread.

  Confirmed

- The *daily-driving-distance* of an EV owner depends on a random generated value at model initialisation. Depending on this value, the EV owner receives a *daily-driving-distance* compatible with this random value. Model initialisation printed n = 0.4994. Corresponding daily-driving-distance should be 10 + random 10. EV owner has a *daily-driving-distance* of 16.

  Confirmed

Appendix C.1.2 Sanity checks Platform initialisation

- Depending on the model user's design decisions regarding level-of-decentralisation, data-storage-method, blockchain-configuration, and consensus-protocol, the platform should inherit the corresponding values for system-performance, system-flexibility, required-skill, and fundamental-properties. Table 35 contains the initialised design setup as well as the corresponding values for the system specifics.

Design setup	System-performance	System-flexibility	Required-skill	Fundamental-properties
Decentralised	0.1	0.1	0.2	0.3
On-chain smart contracts	0.2	0.1	0.2	0.3
Public	0.1	0.1	0.1	0.1
Proof-of-work	0.1	0.1	0.1	0.3
Total	**0.5**	**0.4**	**0.6**	**1**

TABLE 35 SANITY CHECKS PLATFORM INITIALISATION CONFIGURATION VALUES

The following lines of code were used to calculate the values within the model.

Sum [system-performance] of platforms	outcome: 0.5 **confirmed**
Sum [system-flexibility] of platforms	outcome: 0.4 **confirmed**
Sum [required-skill] of platform	outcome: 0.6 **confirmed**
Sum [fundamental-properties] of platforms	outcome: 1 **confirmed**

Appendix C.1.3 Sanity checks establish social influence of EV owners

- The social influence value of EV owners should be equal to the exponential increase of either 0.5 + *fraction-of-agents-using-system* or 1.5 – *fraction-of-agents-using-system* depending on which of both is the lowest value. This value is then multiplied by the mean-skill-of-system-users. A model run reported 0.2855 as the *social-influence-value.* The fraction-of-agents-using-system is equal to 0.07. The mean-skill-of-system-users is equal to 0.8788. the exp-network-effects is initialised as 2. Therefore the social-influence-value should be 0.8788 * ((0.5 + 0.07) * (0.5 + 0.07)) = 0.2855.

  Confirmed.

Appendix C.1.4 Sanity checks skill increase of EV owners

- *Skill* increase of an EV owner which uses the system is determined by the *min-skill-att-value* multiplied by 1 – the *skill* of the agent multiplied by the *skill-delinearisation-value*. This value is then multiplied by the *social-influence* and the *intelligence* of the agent. A model run is initialised. A single agent is asked to show its initial values which this agent uses to calculate its skill increase.

```
Agent is a system user
Social-influence value = 0.08995
Intelligence = 0.9229
Skill = 0.88423
Skill after increase = 0.88615
Min-skill-att-value = 0.05
Skill-delinearisation-value = 0.2
```

According to these values, the skill should increase by ((1 – 0.88423) * 0.2 * 0.08995 * 0.9229) = 0.00192. The skill of the agent has increased by 0.88615 – 0.88423 = 0.00192.

Confirmed

- *Skill* increase of an EV owner which doesn't use the system is determined by the *min-skill-att-value* multiplied by the *social-influence* and the *intelligence* of the EV owner. A model run is initialised. A single agent is asked to show its initial values which this agent uses to calculate its skill increase.

Agent is not a system user Social-influence value = 0.060899 Intelligence = 0.29407 Skill = 0.90456 Skill after increase = 0.90545 Min-skill-att-value = 0.05

According to these values, the skill should increase by (0.05 * 0.060899 * 0.29407) = 0.000895. The skill of the agent has increased by 0.90545 – 0.90456 = 0.00089.

Confirmed

Appendix C.1.5 Sanity checks system usage of EV owners

- *Performance-expectancy* is calculated according to the following formula:

$$Performance\_exp = \omega * \frac{\alpha(S) * \frac{\vartheta}{\theta}}{a} * \varphi * \sigma * (\beta - \tau) - \left(\frac{\gamma}{\frac{\alpha}{a(S)}} \right)$$

The lines of code presented in table 36 were implemented in the model to identify the values needed in order to calculate the *performance*-expectancy of an agent in the system. According to the above stated formula the *performance-expectancy* should be equal to (0.85424 * 0.5 * 0.70569 * 0.5) – 0.13765 = 0.01305.

Confirmed

Netlogo code	*Response*
print "my skill is" print skill	0.85424
print "the comparison supply PCP is" print comparison-supply-PCP	0.5
print "the number of users is" print count EVowners with [uses-system? = true]	2
print "the system supply is" print system-supply	1235.305
print "the system demand is" print system-demand	6061.57
print "number of EVowners is" print count EVowners	38
print "my intelligence is" print intelligence	0.70569
print "the system performance is" print sum [system-performance] of platforms	0.5
print "my personal pattern performance is" print personal-pattern-performance-factor	-0.13765
print "the fraction higher charging patterns is" print fraction-higher-charging-patterns	0
print "my performance expectancy is" print performance-expectancy	0.01305

TABLE 36 VERIFICATION CODE FOR PERFORMANCE EXPECTANCY

- The *effort-expectancy* of an agent can be calculated in twofold depending on the system-flexibility of the platform. The *effort-expectancy* of an EV owner is monitored and was equal to -0.7153 at a certain point during the model run. The skill of this agent was equal to 0.9403. The *system-flexibility* was equal to 0.55 and the *required-skill* for platform usage was equal to 0.5. According to the predefined formula for effort-expectancy, the *effort-expectancy* should be 0.5 * (1 – 0.55) – 0.9403 = -0.7153.

  Confirmed

- Whenever the *skill* of an EV owner is higher than the *required-skill* of the platform, this agent becomes enabled to use the platform. Therefore this agent will set its internal state *can-use-system?* To true.

  Confirmed

- Whenever the *effort-expectancy* and *performance-expectancy* are higher than the predefined thresholds in the UI, which are indicated by *performance-threshold* and *effort-threshold*, this EV owner will start using the system. This agent will change its internal state of *uses-system?* To true.

  Confirmed

Appendix C.1.6 Sanity checks Update EV charge of EV owners

- Each tick an EV owner should reduce its *EV-charge* depending on its current *EV-charge*, its *daily-driving-distance* and its *battery-range.* A single agent has an EV-charge of 1, a battery range of 249.26 kilometers and a daily-driving-distance of 44 kilometers. According to the conceptual model. The *EV*-charge after one tick should decrease to ((1 * 249.26) – 44) / 249.26 = 0.8234. The agent reported a value of 0.8234.

  Confirmed

- Whenever the *EV-charge* is lower than the *charging-pattern,* the EV owner will aim to charge its electric vehicle. Therefore, it will change its state of *wants-to-charge?* To true and *wants-to-sell?* To false. Both states changed and the EV owner fully charged its electric vehicle.

  Confirmed

Appendix C.1.7 Sanity checks determine global demand and supply

- The *demand-for-range* should be equal to the sum of the individual demand of all EV owners who aim to charge. The following line of code was implemented to check whether this value was reported accordingly:

*sum [(battery-range – (EV-charge * battery-range))] of Evowners with [(wants-to-charge? = true) and (uses-system? = true)]*

  The reported value was equal to 13496, which was equal to the reported local variable of demand-for-range.

  Confirmed

- The *range-supply* should be equal to the sum of the individual supply of all EV owners who want to sell. The following line of code was implemented to check whether this value was reported accordingly: sum [((EV-charge * battery-range) - (battery-range * charging-pattern))] of EV owners with [(wants-to-sell? = true) and (uses-system? = true)]. An error was found within the code. Supply was not properly calculated. The calculation was altered to exclude those agents which are not system users.

  Resolved

Appendix C.2 Breaking the agent

Extreme effort-threshold

- Negative *effort-threshold* value. Hypothesis: The lower the *effort-threshold*, the least effort is accepted by the EV owners in the system. Therefore, it is expected when the *effort-threshold* is negative, few EV owners will actually use the system. Model output: No EV owners started using the system because their expected effort was higher than the *effort-threshold.*

  Confirmed

- High *effort-threshold* value. Hypothesis: The higher the *effort-threshold*, the more effort is accepted by the EV owners in the system. Therefore, it is expected when the *effort-threshold* is high, no EV owners are limited by the *effort-expectancy* component determining system usage. *Effort-threshold* was initiated with a value of 1000. The following lines of code were implemented to monitor whether no EV owners were limited by the *effort-expectancy* component:

count EVowners with [effort-expectancy > effort-threshold]

  A total of 0 EV owners had an *effort-expectancy* higher than the *effort-threshold.* No EV owners were limited by the *effort-expectancy* component.

Confirmed

Extreme performance-threshold

- Negative *performance-threshold* value. Hypothesis: A negative *performance-threshold* implies that EV owners are willing to accept a very low value of overall system performance. It is expected that EV owners are not limited by the performance of the system when determining system usage, therefore, higher levels of users are expected. *Performance-threshold* was initiated with a value of -1000. Model output: All enabled EV owners are system users.

  Confirmed

- High *performance-threshold* value. Hypothesis: A high *performance-threshold* implies that users expect a high amount of performance from the system. *Performance-threshold* was initiated with a value of 1000. The following lines of code were implemented to monitor whether any EV owners reach the level of 1000 *performance-expectancy*:

  - *count EVowners with [performance-expectancy > performance-threshold]*

  A total of 0 EV owners had an *performance-expectancy* higher than the *performance-threshold.* No EV owners started to use the system.

  Confirmed

Extreme skill values

- Negative *skill* value. Hypothesis: A negative *skill* value implies that all EV owners within the system have a skill level below 0. Since the *required-skill* for platform usage is a positive value at all times, no EV owners are enabled to use the system. Since no EV owners use the system, *skill* cannot increase. *Skill* was initiated with a value of -1000. Model output: No enabled EV owners and skill remains linear.

  Confirmed

- High skill value. Hypothesis: A high *skill* value implies that all EV owners within the system have a skill level higher than the *required-skill* for platform usage. Therefore, all agents are enabled to use the system at system initialisation. *Skill* was initiated with a value of 1000.

  The model presented an error: *Math operation produced a number too large for Netlogo*. The calculations of *social-influence-value* were balanced around a *skill* value between 0 and 1. Logically, a *skill* value above 1 was not possible. Before the error occurred, all but a few EV owners used the system.

  Confirmed

Appendix C.3: Interaction testing in a minimal model

Minimal model testing concerns with verifying the basic interaction between a minimal number of agents. First, one agent of each type is initiated in order to verify the basic interaction between the smart charging platform and a potential user. When platform-user interaction is verified, an extra potential user is initiated to verify whether both users interact with each other. The interaction between the platform and an EV owner is limited and mostly indirect. Therefore it is decided to initiate 2 EV owners and examine the interaction between these agents.

Appendix C.3.1 Trade electricity between EV owners

Whenever an EV owner wants to charge its EV, this EV owner will actively search for a single EV owner which can supply the demand. When such an EV owner is found, both EV owners will trade electricity, implying one EV owner will decrease its *EV-charge* relatively to the other EV owner increasing its *EV-charge.* Two EV owners are initiated. Both are initiated in a way that ensures that both use the system.

When monitoring the behaviour of both agents a peculiar error was found. The EV-charge of one EV owner was equal to its charging-pattern. The code was not written to handle this particular situation. The following alteration was made:

ifelse EV-charge = charging-pattern changed to: *ifelse EV-charge <= charging-pattern*

EV owner 1 has an *EV-charge* of 0.6997 (242.35 kilometers) when it tries to charge its EV to 1. EV owner 2 has a fully charged EV and will aim to sell its electricity. It sells 0.1403 of EV-charge to EV owner 1, which is the equivalent of 53.75 kilometers. The EV-charge of EV owner 1 is increased to (242.35 + 53.75) 296.1 kilometers. The total EV-charge capacity of EV owner 1 is equal to 346.35. Therefore, EV owner 1 has to buy (346.35 – 296.1) 50.25 kilometers from the electricity grid. EV owner 1 reported that it bought 50.248 kilometers from the grid.

Confirmed

Appendix C.3.2 Determine ethical implications

This section identifies whether the conceptual formulas for calculating ethical implication values as presented in chapter five, were properly transposed to computer readable code. This is done by calculating the value for an ethical value at a certain point during a model run by hand. This value should match the value presented by Netlogo.

- Verification of privacy implications calculations

$\alpha(S)$:	All users which use the system
α :	All users in the model environment
β :	The fundamental properties of the system based on technology layout
I:	Initial score based on best alternative

$$privacy_{score} = I - \sum \frac{\alpha(S)}{\alpha} * \beta$$

According to the formula and a decentralised platform with an on-chain smart contracting data storage, the privacy-score should be *0.755 (0.9 – (29/200 * 1))*

Confirmed

- Verification of security implications calculations

γ: The effectiveness of the consensus algorithm: 0.045
β: The fundamental properties of the system based on technology layout: 1
δ: Supplement based on design effectiveness: 0.3

$$Security\_score = \gamma * \beta + \delta$$

According to the formula and a decentralised platform with an on-chain smart contracting data storage and a proof-of-work consensus algorithm, the security-score should be *0.345 (0.045 * 1 + 0.3)*

Confirmed

- Verification of trust implications calculations

β: The fundamental properties of the system based on technology layout: 1
$\alpha(S)$: All users which use the system: 30
α: All users in the model environment: 200
θ: Fundamental properties based on the technological layout: to be calculated
ε: Supplement for best design: 0.5

Subject to:

$$\theta = \beta * \varepsilon$$

If linear subject to:

$$Trust\_score = \theta + \frac{\alpha(S)}{a}$$

If non-linear subject to:

$$Trust\_score = \theta + \left(\frac{\alpha(S)}{a} * 2\right)^2$$

According to the formula and a decentralised, public platform with on-chain data storage and a proof-of-work consensus algorithm, the trust-score should be *0.59 (1 * 0.5 + (30 * 2/200) ^ 2)*

Confirmed

- Verification of confidentiality implications calculations

ρ :	number of transactions this day (tick): 160
σ :	total number of platform trades: 6321
τ :	compensation factor for optimal designs: 2
ε :	total number of days the system is implemented: 58 - 1

$$Confidentiality_{score} = 1 - \frac{\frac{\rho * \varepsilon}{\sigma}}{\tau} * 0.5$$

According to the formula and a decentralised, public platform with on-chain data storage and a proof-of-work consensus algorithm, the confidentiality-score should be *0.639 (1 – (((160 * 57 / 6321) / 2) * 0.5))*

Confirmed

- Verification of anonymity implications calculations

α :	number of users in the system: 200
β :	The mean number of peers a platform user has: 5
γ :	The number of system users: 34
δ :	The fundamental properties of the system layout: 0.8
ε :	A compensation factor for the best possible design: 0.25

$$Anonymity\_score = 1 - \frac{\frac{\gamma}{\alpha}}{\left(\frac{2}{\beta}\right)} * \delta * \varepsilon$$

According to the formula and a decentralised, public platform with on-chain data storage and a byzantine fault tolerance consensus algorithm, the confidentiality-score should be *0.915 ((34 / 200 / (2 / 5)) * 0.8 * 0.25)*

Confirmed

Appendix C.4: Multi-agent verification
The last step in model verification entails verifying the interaction between multiple agents under normal operating inputs. Apart from verifying agent interaction, this verification steps aims at identifying expected emergent patterns in line with the implemented concepts.

C.4.1. Trade electricity between multiple agents
Whenever an EV owner wants to charge its EV, and a single EV owner cannot supply this demand, the EV owner will actively search for an arrangement of EV owners which can supply the demand. This is done by iterating over a list of EV owners with the highest supply capacities. Three EV owners use the system. EV owner 1 has a positive daily-driving-distance and will at some point in time aim to charge it EV. EV owner 2 and 3 have a daily-driving-distance of 0 and will therefore retain a EV-charge of 1. EV owner 1 will aim to charge at an EV-charge level of 0.58593, which is the equivalent of 227.5 kilometers. EV owner 1 is aiming to buy (388.3 – 227.5) 160.8 kilometers of EV-charge. EV owner 2 can offer ((1 – 0.884) * 256.95) 29.8 kilometers. EV owner 3 can offer ((1 – 0.8777) * 290.48) 35.525 kilometers. Therefore, EV owner 1 can buy a total of (35.525 + 29.8) 65.33 kilometers. EV owner 1 will buy (160.8 – 65.33) 95.5 kilometers from the electricity grid.

Confirmed

Appendix C.5 Theoretical prediction
C.5.1. Flattening of Skill increase
One of the concepts introduced for this thesis, is the de-linearisation of skill increase. This de-linearisation depends on the *skill* value of EV owners. Since the EV owners are heterogeneous, *skill* de-linearisation differs for every EV owners. However, the mean value of *skill* over time is expected to flatten.

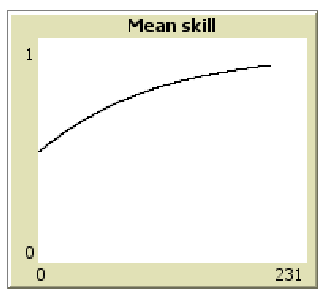


FIGURE 54 THEORETICAL PREDICTION PLOT - MEAN SKILL OF EV OWNERS

C.5.2 mean charging-pattern of system users
Hypothesis: A lower *charging-pattern* is beneficial when the number of system users is lower as this type of charging behaviour is more applicable to a smart charging environment. However, as EV owners start using the system, higher *charging-pattern* values decide on using the system. It is expected that over time, the mean charging-pattern value of the system users increases. Model output:

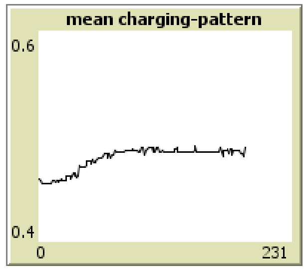


FIGURE 55 THEORETICAL PREDICTION PLOT - MEAN CHARGING PATTERN OF EV OWNERS

C.5.3 Increase in average peers per users

Hypothesis: The mean *charging-pattern* of system users will most likely increase over time due to the increase of users enabling higher *charging-patterns* to partake. EV owners with higher *charging-patterns* aim to charge their EVs at higher levels of *battery-charge*. When these EV owners are able to sell electricity, their relative supply is lower than the supply of EV owners with lower charging-patterns. Therefore, the number of peers needed to fully charge an EV will most likely increase.

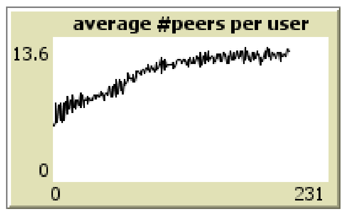


FIGURE 56 THEORETICAL PREDICTION PLOT - AVERAGE NUMBER OF PEERS PER USER

C5.4 Decrease of social influence

As the individual *skill* of an EV owner increases it is expected that the social influence on this EV owner decreases. This is one of the concepts introduced within this thesis. When the system is used, the *skill* of each EV owner will increase over time. Therefore the mean social influence will most likely decrease over time.

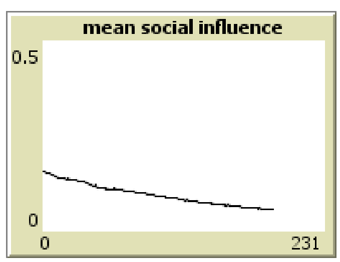


FIGURE 57 THEORETICAL PREDICTION PLOT - MEAN SOCIAL INFLUENCE

Appendix D: ODD+D protocol

Overview	Purpose	- The purpose of this study is to explore different design alternatives for a smart charging system with regards to system-usage and ethical value fulfilment. - The model is designed as a first step in exploring which patterns of interaction emerge when a smart charging platform for smart EV charging is introduced. The model is designed for all those who are interested in the field of V2G appliances and technologies.
	Entities, state variables, and scales	- The model includes two types of entities: EV owners and the smart charging platform. - EV owners have the following attributes: o Skill o Intelligence o Charging pattern o Daily driving distance o Battery range o Effort expectancy o Performance expectancy o Social influence o Indicator for system usage o number of days since system usage o Indicator whether EV owner is enabled to use system o EV charge o Indicator whether EV owner wants to charge o Indicator whether EV owner wants to sell o quantity of kilometers bought from the grid o quantity of kilometers bought from the platform o quantity of kilometers bought this day o Number of platform trades o number of transaction peers this day o Indicator whether the Ev owner has switched - Platforms have the following attributes: o Fundamental system properties o scores for ethical implications o required skill for system usage o system performance o system flexibility - Exogenous factors are: o Value for social influence o System demand in kilometers o System supply in kilometers

		o number of EV owners willing to charge o number of EV owners willing to sell o Total number of transaction peers o Total number of transactions this day o quantity of kilometers bought from platform this day - Reporter variables for model analysis are: o Privacy implications o Trust implications o Security implications o Confidentiality implications o Anonymity implications o Profitability implications regarding transactions o Profitability implications regarding traded kilometers o Total number of users o Total number of enabled users o Mean skill of system users o Mean charging pattern of system users o Mean social influence of EV owners o Mean peers per system user o Fraction traded electricity grid versus platform o Social influence value of system o Mean system usage time o number of switches - Space: each EV owner is placed in a square around the initiated platform. No landscape is initialised. Distribution of EV owners within the square is done randomly. Space is irrelevant. - One time step represents a day in real-world.
	Process overview and scheduling	- Each day, EV owners decide on whether they use the smart EV charging system based on concepts from the capability approach as presented by Sen (1993). They assess whether they are skilled enough to use the system. When so they become enabled to use the system. Thereafter, EV owners decide whether their effort-expectancy is low enough and their performance-expectancy is high enough based on notions from UTAUT. When so they start using the system. When EV owners use the system they can trade electricity with other EV owners based on their respective demand and supply. - When at any point in time the effort-expectancy and performance-expectancy of an EV owner drops bellow the threshold, this EV owner will stop using the system.

Design concepts	Theoretical and empirical background	Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the levels of the sub-model (apart from the decision model)? - Capability approach as presented by Sen (1993) is used as the main theoretical framework from which the following aspects are borrowed: o Sequence of decision making o Identification of interaction between conversion factors, system usage, social context, and preference mechanism - Concept of networking effects as presented by Hall and Khan (2003) is used to describe skill increase of EV owners. - Four constructs within UTAUT (Venkatesh et al., 2012) are used to identify whether the platform is of added-value for an EV owner. The four constructs are: o Performance expectancy o Effort expectancy o Social influence o Facilitating conditions - Blockchain taxonomy as presented by Xu et al. (2017) is used to identify the differences between platform design layouts. - Agent-based modeling is used as research method and Netlogo is used as simulation software - Exploratory modeling and analysis as presented by Kwakkel and Pruyt (2013) is used to explore different uncertain scenarios on which design decisions have to be made.
	Individual decision making	- EV owners decide on whether the expected system performance and their effort expectancy are acceptable with regards to the added-value of system usage - Their decision-making rests upon the four constructs from UTAUT within a decision making sequence based on the capability approach. - EV owners adapt their behaviour when their EV charge drops below their accepted charging level. At this point EV owners actively aim to charge their EV. - Generally speaking, the platform is successful when it has a high number of users combined with high system performance, while safeguarding ethical values. - EV owners are pressured by social norms represented by a social influence which is established based on the number of system users.
	Learning	- Collective learning is represented by an increased social experience level due to the indirect sharing of system knowledge. Overall higher social-influence levels are experienced due to higher numbers of system users.
	Individual sensing	- Due to the nature of smart contracting, EV owners are unable to sense elements of other EV owners. However, in line with

		coding logic, EV owners are able to sense the following elements of other EV owners: o Whether the EV owner is a system user o Level of EV charge o Daily driving distance of an EV owner o Charging pattern of an EV owner - The aforementioned sensing elements are used when EV owners aim to charge their EV and are matched to another EV owner. The elements are used in calculating how much electricity is transferred between both EV owners.
	Individual prediction	- Information achieved by EV owners is established on time of execution. Therefore, no future predictions are included within the model
	Interaction	- Direct interactions are: o Electricity trading influenced by other agent's EV charge, charging pattern, battery range, and daily driving distance. - Indirect interactions are: o Social influence due to increase/decrease of number of system users and mean skill of system users. o Changes in performance expectancy due to increase/decrease of system supply, system demand, system performance, charging patterns of other system users, number of system users - Both direct and indirect interactions are influenced by the changing structure of the network of system users. Since all EV owners are heterogeneous, the network layout is unpredictable.
	Collectives	- Three collectives exist within the modeling environment: o EV owners which are not enabled o EV owners which are enabled o EV owners which are system users - All EV owners are initialised as EV owners which are not enabled. All deviations from this initialised group are not imposed by the modeler but emerge from system behaviour.
	Heterogeneity	- EV owners are heterogeneous concerning the following: o Skill o Intelligence o Charging pattern o Daily driving distance o Battery range
	Stochasticity	- Order of action execution among EV owners is random - EV owners are placed randomly within the designated square around the platform - Charging pattern is distributed along a normal distribution - Battery range is distributed along a normal distribution - Driving distance is distributed along an logarithmic distribution - Skill is randomly distributed among EV owners

<table>
<tr><td></td><td></td><td>- Intelligence is randomly distributed among EV owners
- Initial EV charge is randomly distributed among EV owners</td></tr>
<tr><td></td><td>Observation (Incl. emergence)</td><td>The model has the following output variables:
o number of daily transactions
o quantity of kilometers traded on the platform
o number of enabled users
o number of system users
o performance of the smart charging platform based on number of users and transactional data
o A score for ethical implications
o Mean charging pattern of system users</td></tr>
<tr><td>Details</td><td>Implementation details</td><td>- The model is implemented in Netlogo
- In order to run the model, the Netlogo file is needed
- The following equations are used:

o Equation for calculating the skill increase of a system user:
<table>
<tr><td colspan="2">$Skill\_\text{system\_user} = \omega + ((1 - (\omega * \mathrm{L})) * \varphi * \theta)$</td></tr>
<tr><td>ω</td><td>Skill of the agent at previous instance</td></tr>
<tr><td>φ</td><td>Intelligence of the agent</td></tr>
<tr><td>θ</td><td>Social influence on this agent</td></tr>
<tr><td>L</td><td>Skill delinearisation value</td></tr>
</table>

o Equation for calculating the skill increase for non-users
<table>
<tr><td colspan="2">$Skill\_\text{non\_system\_user} = \omega + (\tau * \varphi * \theta$</td></tr>
<tr><td>ω</td><td>Skill of the agent at previous instance</td></tr>
<tr><td>φ</td><td>Intelligence of the agent</td></tr>
<tr><td>θ</td><td>Social influence on this agent</td></tr>
<tr><td>τ</td><td>Minimum skill increase factor</td></tr>
</table>

o Equation for calculating the performance expectancy when no system users exist
<table>
<tr><td colspan="2">$Performance\_exp = \omega * \varphi * \sigma * \mu$</td></tr>
<tr><td>ω</td><td>Skill of potential user</td></tr>
<tr><td>φ</td><td>Intelligence of the potential user</td></tr>
<tr><td>σ</td><td>System performance of the platform</td></tr>
<tr><td>μ</td><td>Moderator value for lack of users</td></tr>
</table>
</td></tr>
</table>

- Equation for calculating the performance expectancy when there are other system users

$$Per_{exp} = \omega * \frac{\alpha(S) * \frac{\vartheta}{\theta}}{a} * \varphi * \sigma + (\beta - \tau) - \left(\frac{\gamma}{\frac{\alpha}{\alpha(S)}} \right)$$

ω	Skill of potential user
φ	Intelligence of the potential user
σ	System performance of the system
$\alpha(S)$	number of system users
θ	System supply
ϑ	System demand
α	number of EV owners in model environment
β	Mean charging pattern of system users
τ	Charging pattern of the potential user
γ	Fraction of higher charging patterns in the system

- Equation for calculating effort expectancy when the platform has a certain degree of flexibility

$$Effort_{expectancy} = \left(\beta * (1 - \delta)\right) - \omega$$

β	Required skill for using the platform
ω	Skill of the agent
δ	System flexibility of the technology layout

- Equation for calculating effort expectancy when the platform has no flexibility

$$Effort_{expectancy} = \beta - \omega$$

β	Required skill for using the platform
ω	Skill of the agent

- Equation for calculating privacy score

$$privacy_{score} = I - \sum \frac{\alpha(\mathrm{S})}{\alpha} * \beta$$

$\alpha(S)$	All users which use the system
α	All users in the model environment
β	The fundamental properties of the system based on technology layout
I	Initial score based on best alternative

- Equation for calculating security score

$$Security\_score = \gamma * \beta + \delta$$	
γ	The effectiveness of the consensus algorithm
β	The fundamental properties of the system based on technology layout
δ	Supplement based on design effectiveness

- Equation for calculating initial trust score concerning an exponential effect

$$Trust\_score = (\beta * \varepsilon) + \left(\frac{\alpha(S)}{a}\right)^2$$	
β	The fundamental properties of the system based on technology layout
α(S)	All system users
α	All users in the model environment
ε	Supplement for best design alternative

- Equation for calculating trust score concerning a linear effect

$$Trust\_score = (\beta * \varepsilon) + \frac{\alpha(S)}{a}$$	
β	The fundamental properties of the system based on technology layout
α(S)	All system users
α	All users in the model environment
ε	Supplement for best design alternative

- Equation for calculating confidentiality score

$$Confidentiality_{score} = 1 - \frac{\frac{\rho * \varepsilon}{\sigma}}{\tau} * 0.5$$	
ρ	number of transactions this day (tick)
σ	total number of platform trades
τ	compensation factor for optimal designs
ε	total number of days the system is implemented

<table>
<tr><td></td><td></td><td>

- Equation for calculating anonymity score

<table>
<tr><td colspan="2">

$$Anonymity\_score = 1 - \frac{\frac{\gamma}{\alpha}}{\left(\frac{2}{\beta}\right)} * \delta * \varepsilon$$

</td></tr>
<tr><td>α</td><td>Number of users in the model environment</td></tr>
<tr><td>β</td><td>mean number of peers a platform user has:</td></tr>
<tr><td>γ</td><td>The number of system users</td></tr>
<tr><td>δ</td><td>The fundamental properties of the system layout:</td></tr>
<tr><td>ε</td><td>A compensation factor for the best possible design</td></tr>
</table>

</td></tr>
<tr><td></td><td>Initialisation</td><td>- At initialisation, 200 EV owners are placed within the demarcated system of which none are yet enabled or system users.</td></tr>
<tr><td></td><td>Input data</td><td>- Several types of input data are used:
o Input data for charging pattern spread
o Input data for battery range
o Input data for daily driving distance
o Input data for effects of blockchain design</td></tr>
<tr><td></td><td>Submodels</td><td>- No sub-models</td></tr>
</table>

Appendix E: Model experimentation data

This appendix presents all graphs that were produced with model experimentation. An overview of the parameterisation of the experiment is displayed supplemented by the various graphs linked to this parameterisation. Take note that the data was acquired using EMA techniques and that each scenario is therefore unique. It is therefore hard to replicate the exact data as presented in this section. However, a comparable setup should provide comparable outcomes nonetheless.

Appendix D.1: Design layout 1 experimentation data

Affinity	*Parameter*	*setting*
Standard model settings	*Level_of_decentralisation*	[centralised]
	Data_storage_method	[off_chain_data_storage]
	Blockchain_configuration	[private]
	Consensus_protocol	[byzantine_fault_tollerance]
	Number_of_EV_owners	[200]
	Charging_pattern_spread	[0.5]
	Battery_range_spread	[50]
	Exp_network_effects	[2]
	Comparison_supply_PCP	[0.5]
EMA settings	Performance_threshold	[0.01 – 0.025]
	Effort_threshold	[-0.5 – 0.3]
	User_absence_compensation	[0.1 – 0.9]
	Min_skill_att_value	[0.05 – 0.2]
	Minimum_skill	[0.1 – 0.7]
	Skill_delinearisation_value	[0.1 – 0.5]
	Intelligence_distribution	[0.9 – 1]

TABLE 37 EXPERIMENTAL DESIGN LAYOUT 1 - PARAMETERS AND SETTINGS

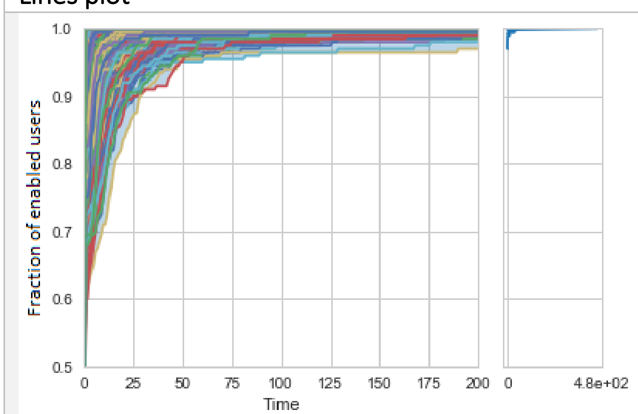
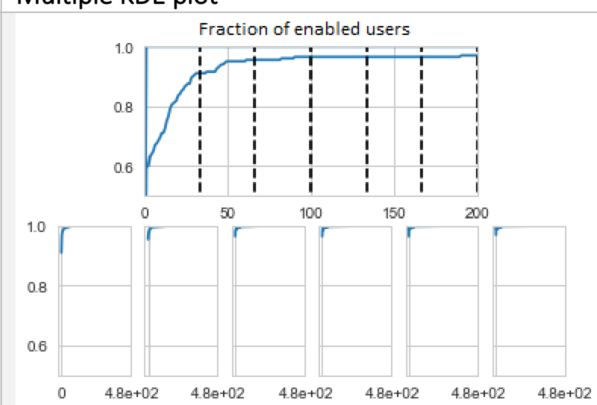
Lines plot	Multiple KDE plot
	

TABLE 38 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – FRACTION OF ENABLED USERS

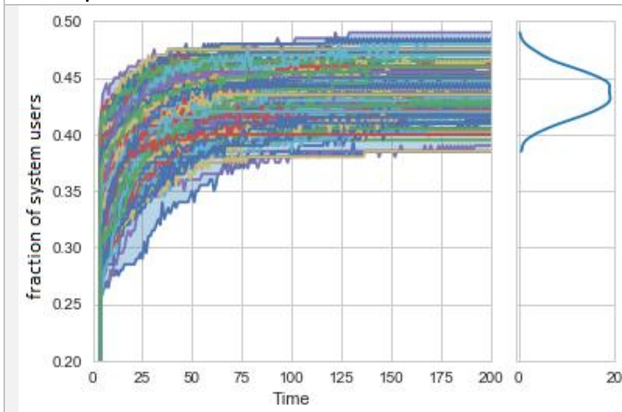
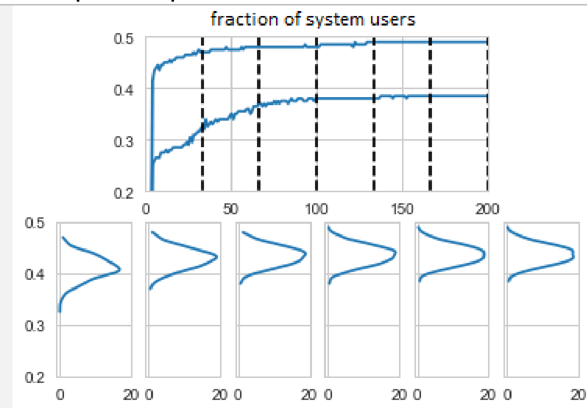
Lines plot	Multiple KDE plot
	

TABLE 39 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – FRACTION OF SYSTEM USERS

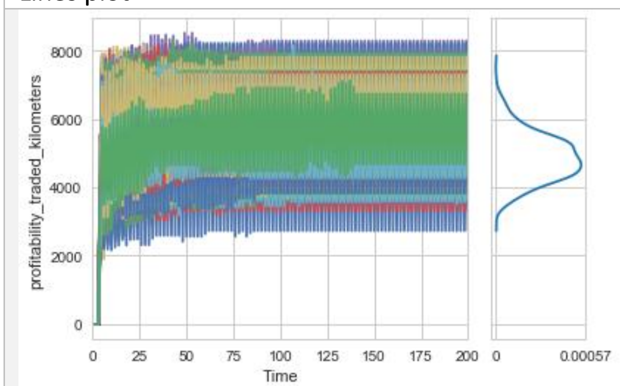
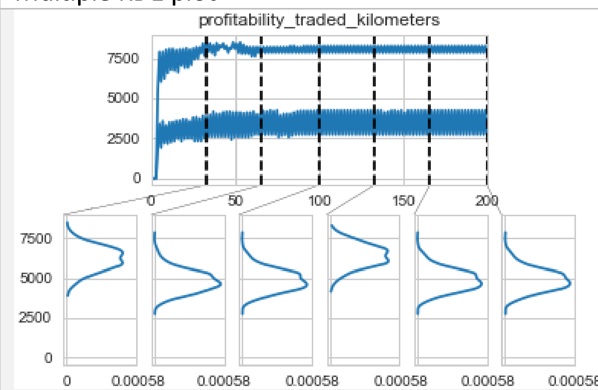
Lines plot	Multiple KDE plot
	

TABLE 40 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – PERFORMANCE TRADED KILOMETERS

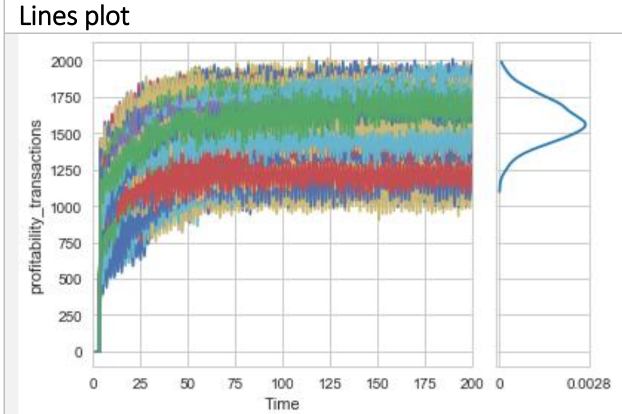
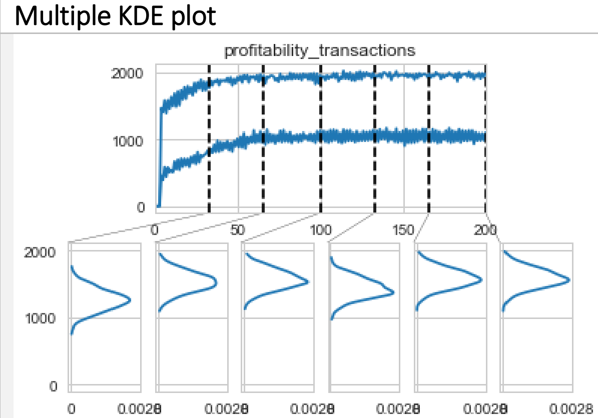
Lines plot	Multiple KDE plot
	

TABLE 41 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – PERFORMANCE TRANSACTIONS

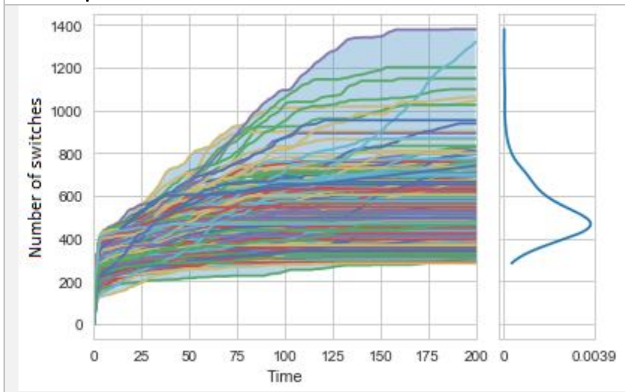
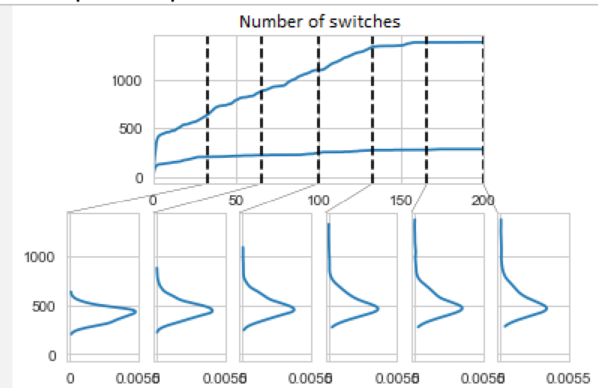
Lines plot	Multiple KDE plot
	

TABLE 42 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – NUMBER OF SWITCHES

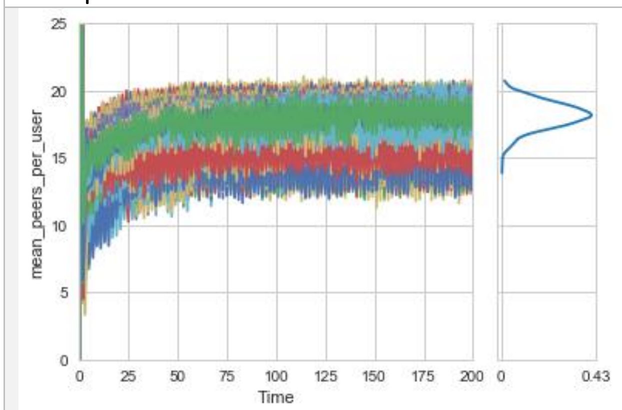
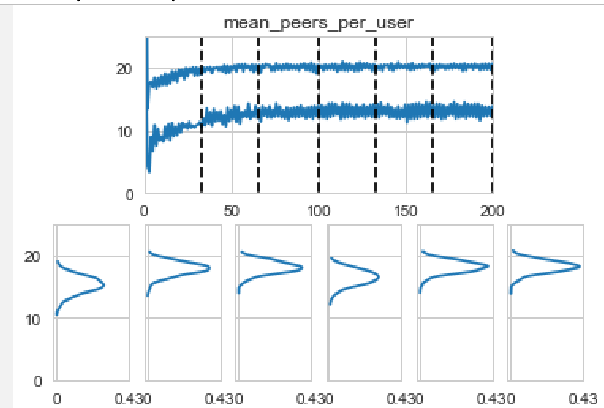
Lines plot	Multiple KDE plot
	

TABLE 43 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – MEAN PEERS PER USER

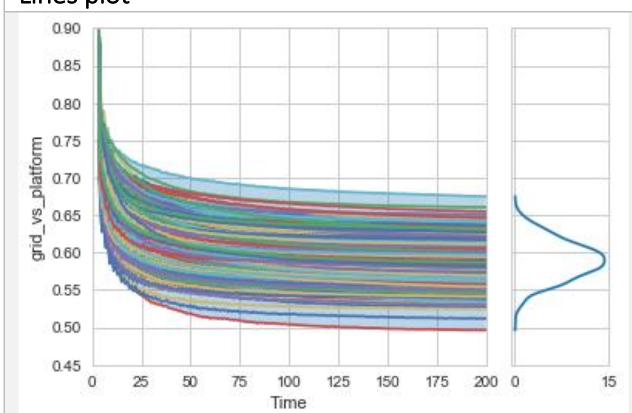
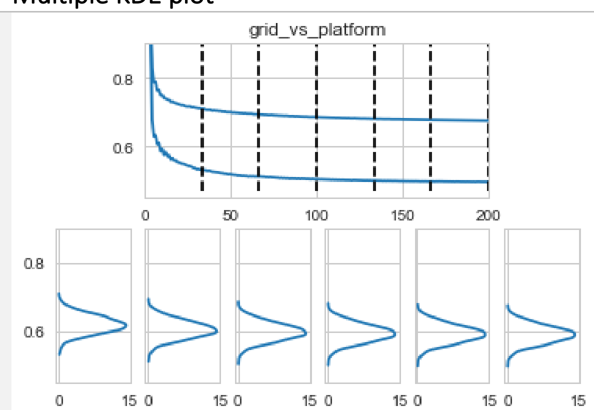
Lines plot	Multiple KDE plot
	

TABLE 44 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – GRID VERSUS PLATFORM

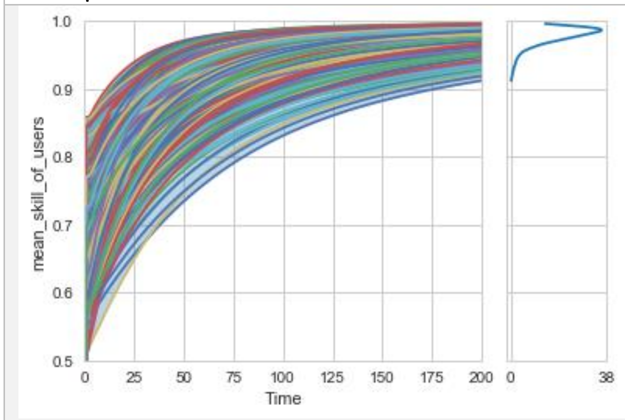
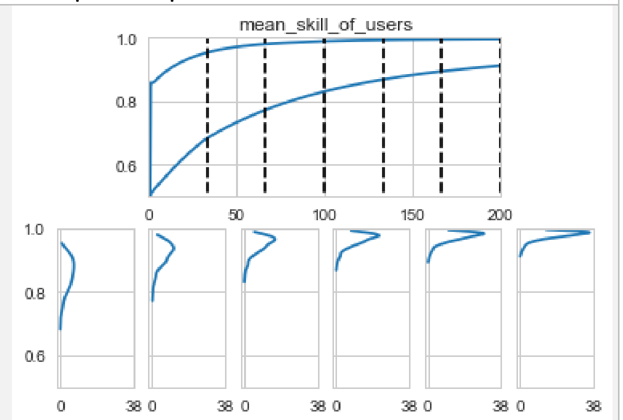
Lines plot	Multiple KDE plot
	

TABLE 45 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – MEAN SKILL OF USERS

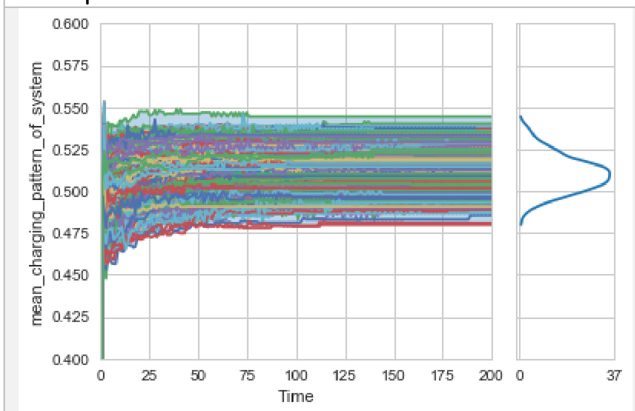
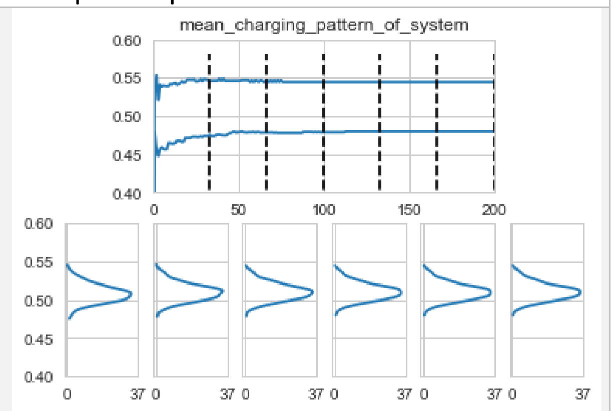
Lines plot	Multiple KDE plot
	

TABLE 46 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – MEAN CHARGING PATTERN OF SYSTEM

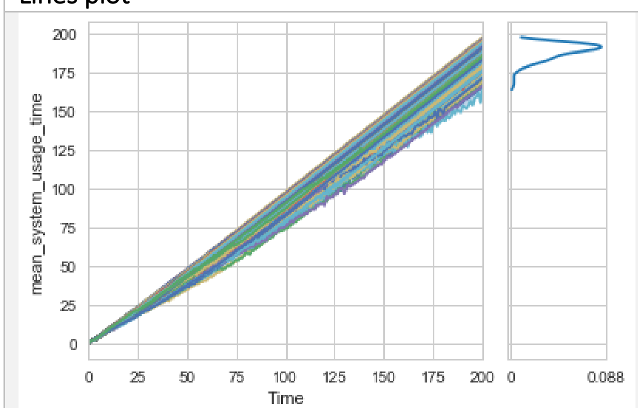
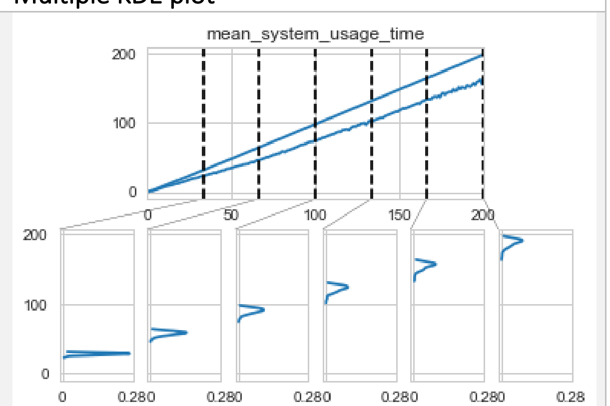
Lines plot	Multiple KDE plot
	

TABLE 47 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – MEAN SYSTEM USAGE TIME

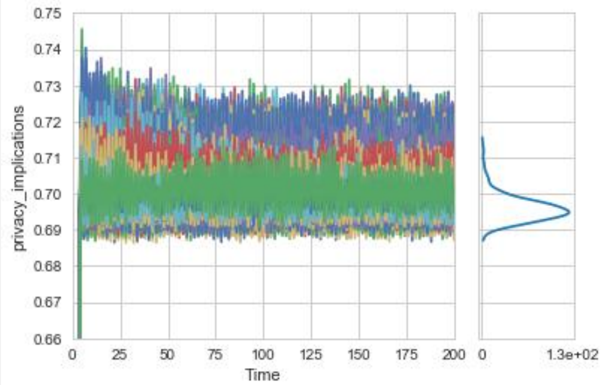
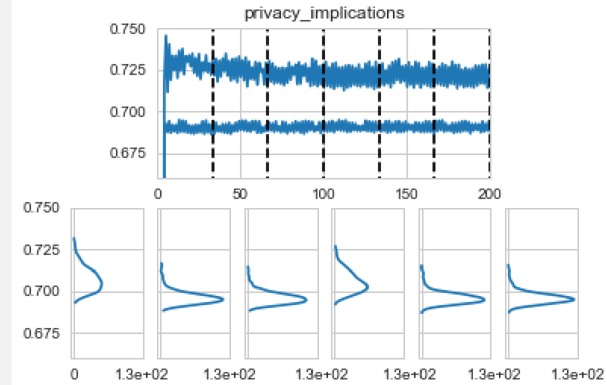
Lines plot	Multiple KDE plot
	

TABLE 48 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – PRIVACY SCORE

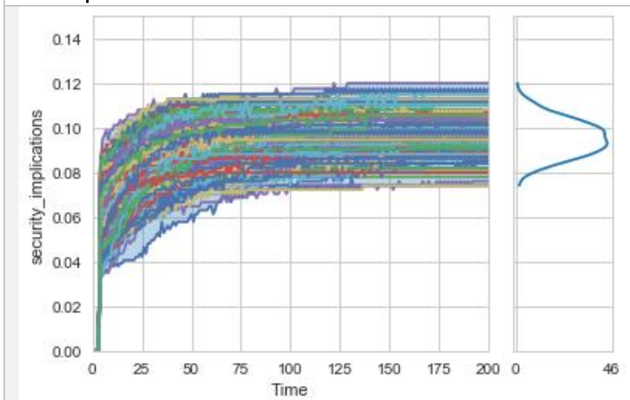
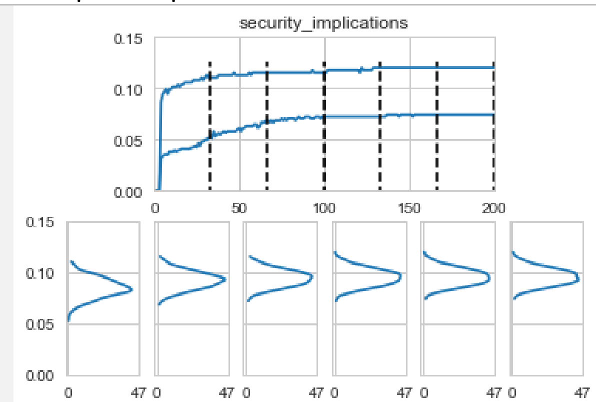
Lines plot	Multiple KDE plot
	

TABLE 49 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – SECURITY SCORE

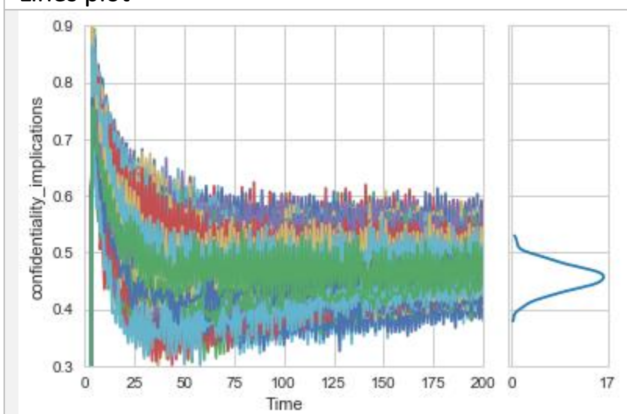
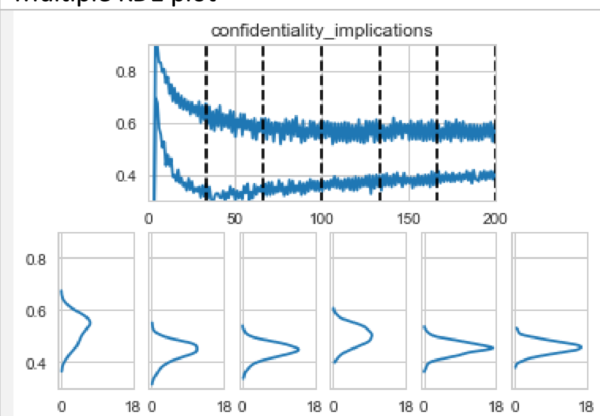
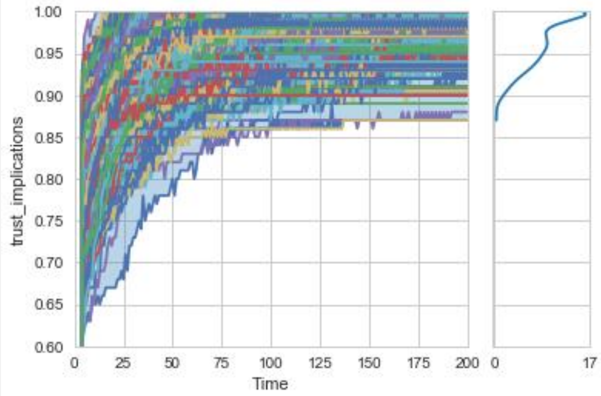
Lines plot	Multiple KDE plot
	

TABLE 50 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – CONFIDENTIALITY SCORE

Lines plot



Multiple KDE plot

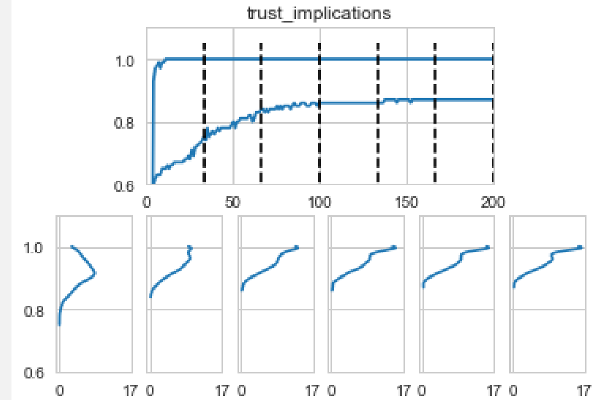
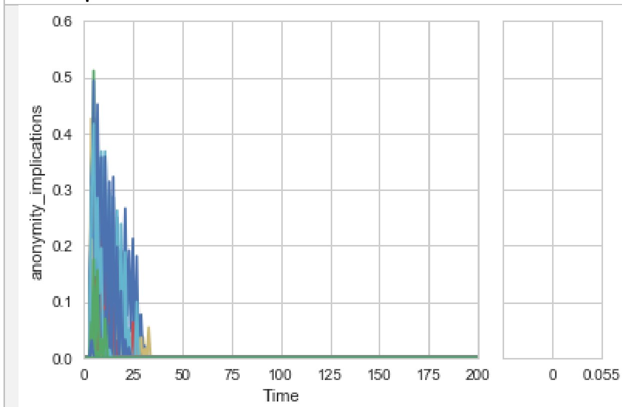


TABLE 51 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – TRUST SCORE

Lines plot



Multiple KDE plot

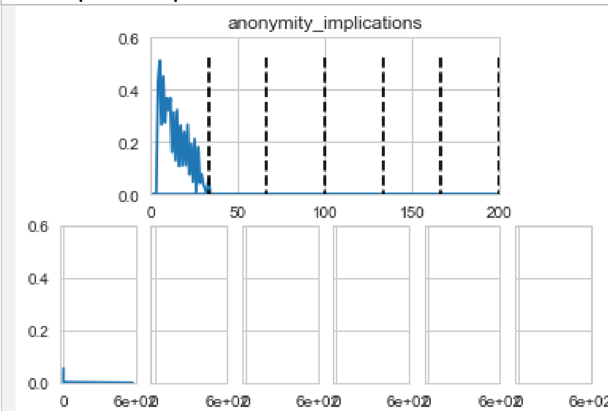
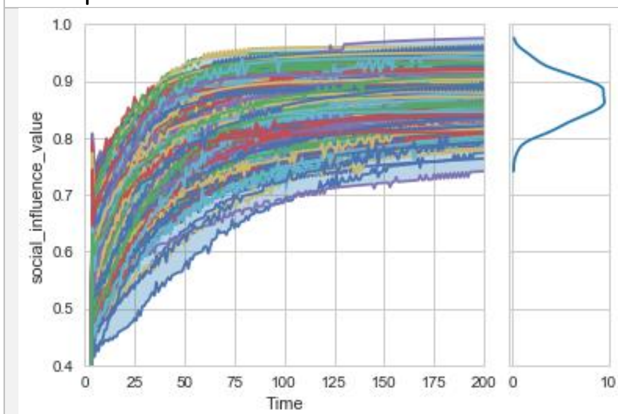


TABLE 52 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – ANONYMITY SCORE

Lines plot



Multiple KDE plot

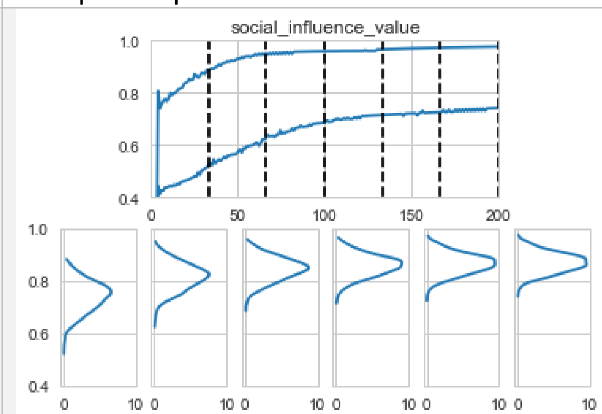


TABLE 53 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – SOCIAL INFLUENCE VALUE

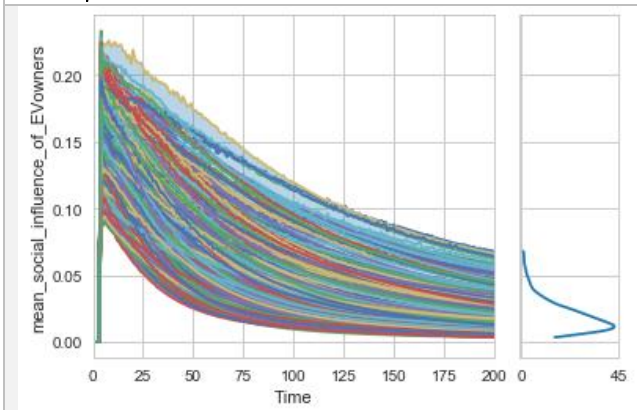
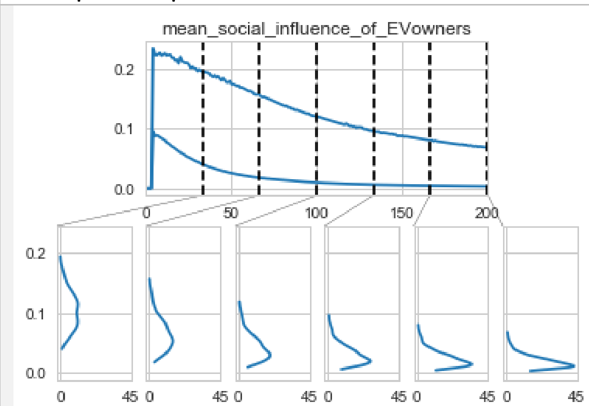
Lines plot	Multiple KDE plot
	

TABLE 54 EXPERIMENTAL OUTCOMES - EXPERIMENT 1 – MEAN SOCIAL INFLUENCE OF EV OWNERS

Appendix D.2: Design layout 2 experimentation data

Affinity	*Parameter*	*setting*
Standard model settings	*Level_of_decentralisation*	[decentralised]
	Data_storage_method	[on_chain_data_storage]
	Blockchain_configuration	[public]
	Consensus_protocol	[proof-of-work]
	Number_of_EV_owners	[200]
	Charging_pattern_spread	[0.5]
	Battery_range_spread	[50]
	Exp_network_effects	[2]
	Comparison_supply_PCP	[0.5]
EMA settings	Performance_threshold	[0.01 – 0.025]
	Effort_threshold	[-0.5 – 0.3]
	User_absence_compensation	[0.1 – 0.9]
	Min_skill_att_value	[0.05 – 0.2]
	Minimum_skill	[0.1 – 0.7]
	Skill_delinearisation_value	[0.1 – 0.5]
	Intelligence_distribution	[0.9 – 1]

TABLE 55 EXPERIMENTAL DESIGN LAYOUT 2 - PARAMETERS AND SETTINGS

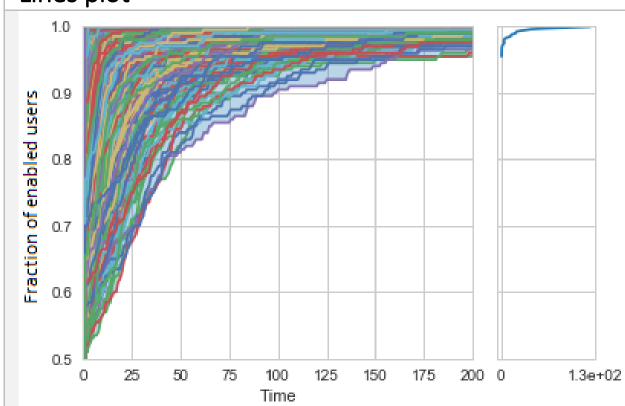
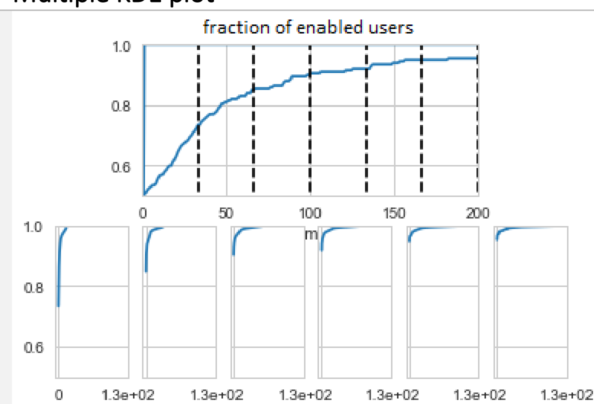
Lines plot	Multiple KDE plot
	

TABLE 56 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – FRACTION OF ENABLED USERS

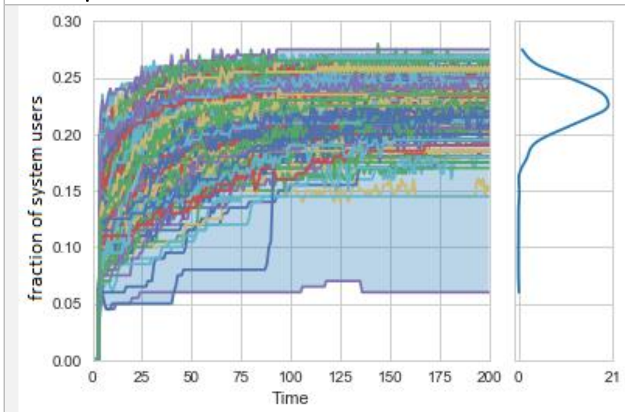
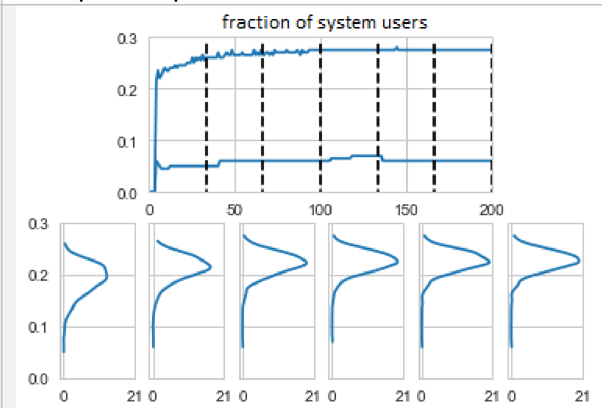
Lines plot	Multiple KDE plot
	

TABLE 57 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – FRACTION OF SYSTEM USERS

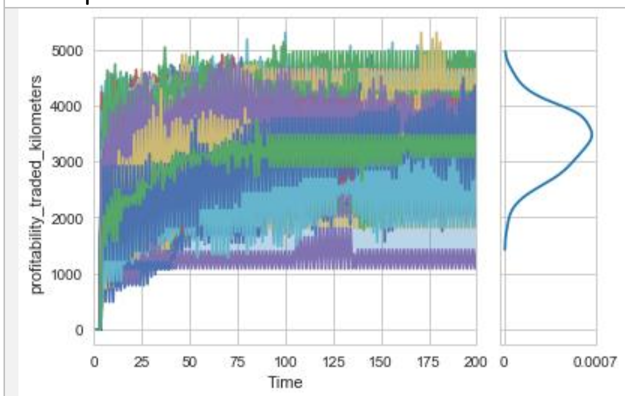
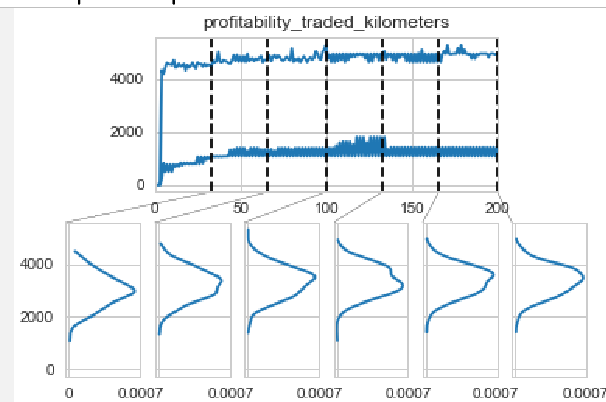
Lines plot	Multiple KDE plot
	

TABLE 58 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 –PERFORMANCE TRADED KILOMETERS

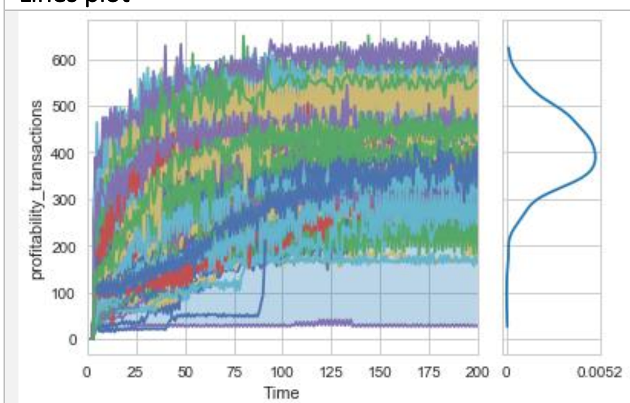
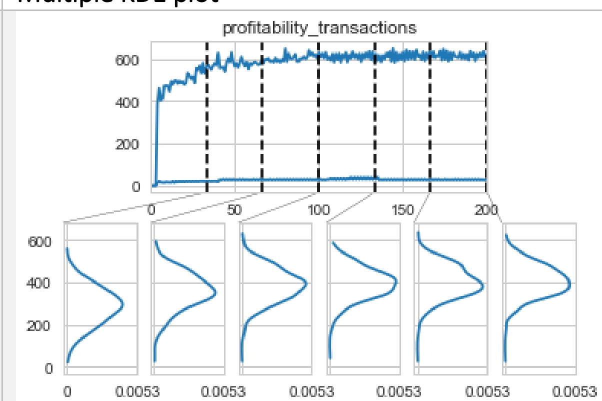
Lines plot	Multiple KDE plot
	

TABLE 59 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – PERFORMANCE TRANSACTIONS

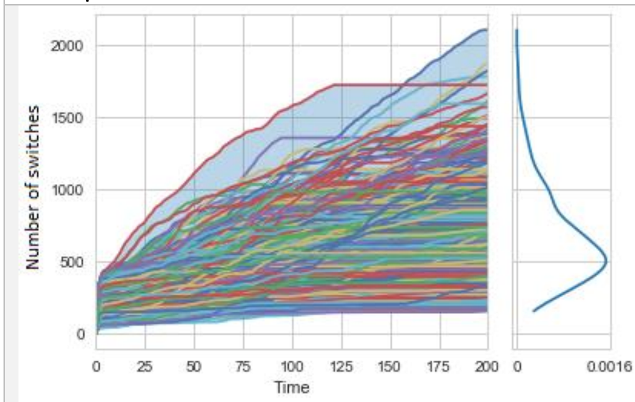
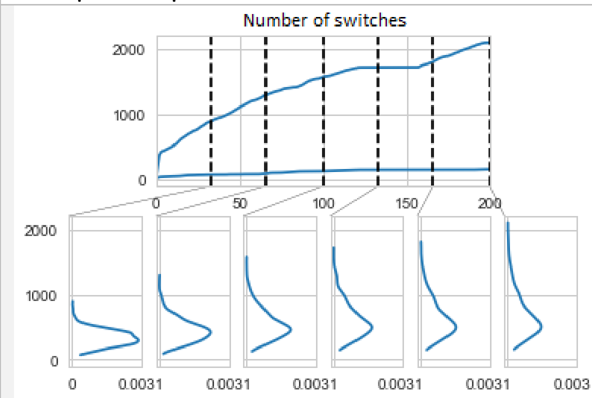
Lines plot	Multiple KDE plot
	

TABLE 60 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – NUMBER OF SWITCHES

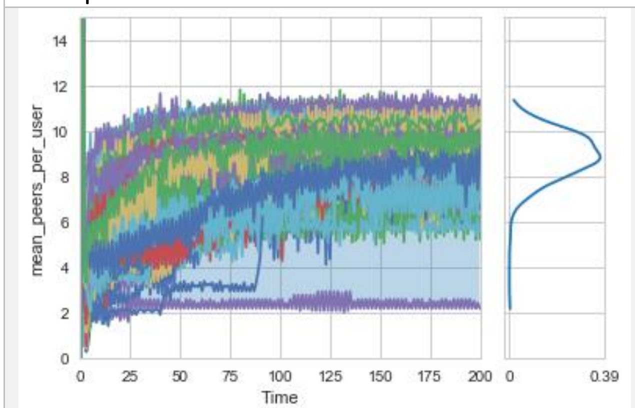
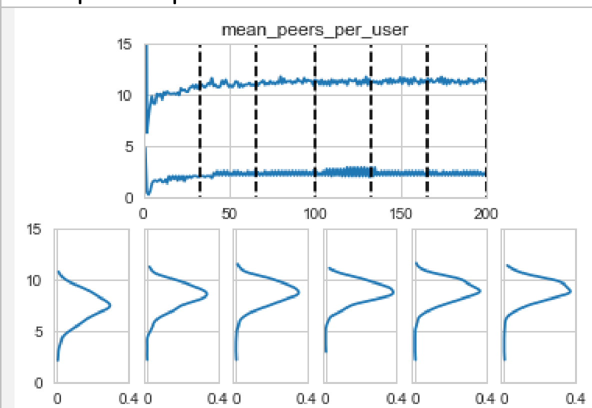
Lines plot	Multiple KDE plot
	

TABLE 61 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – MEAN PEERS PER USER

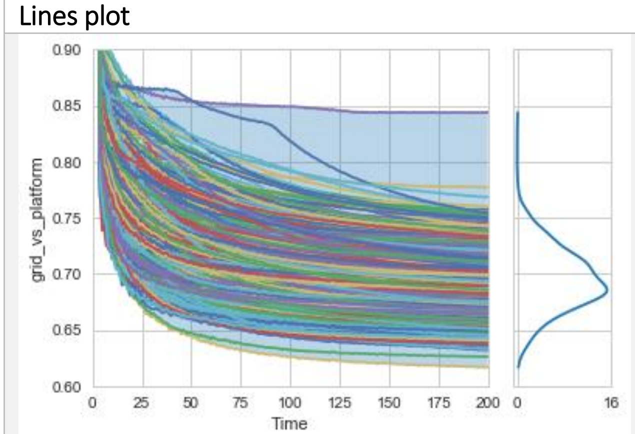
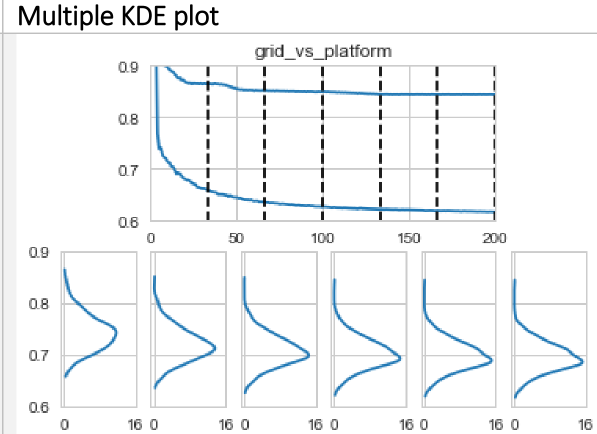
Lines plot	Multiple KDE plot
	

TABLE 62 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – GRID VERSUS PLATFORM

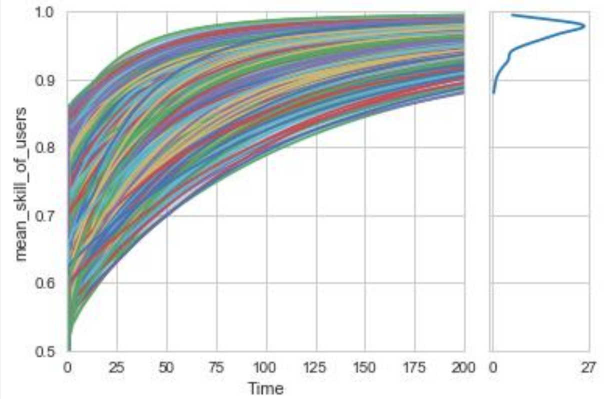
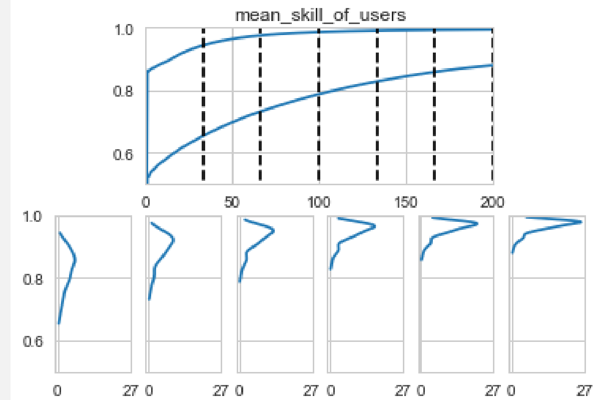
Lines plot	Multiple KDE plot
	

Table 63 Experimental outcomes - Experiment 2 – Mean skill of users

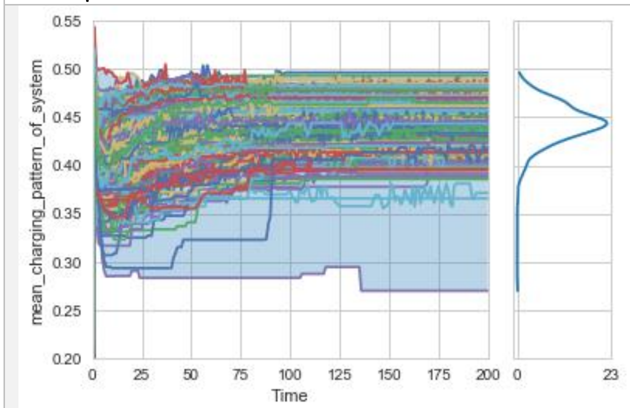
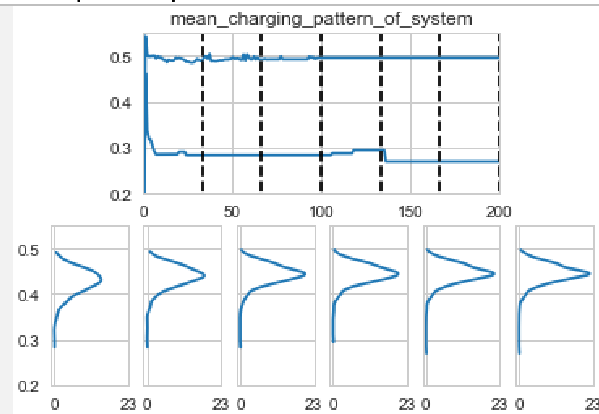
Lines plot	Multiple KDE plot
	

Table 64 Experimental outcomes - Experiment 2 – Mean charging pattern of system

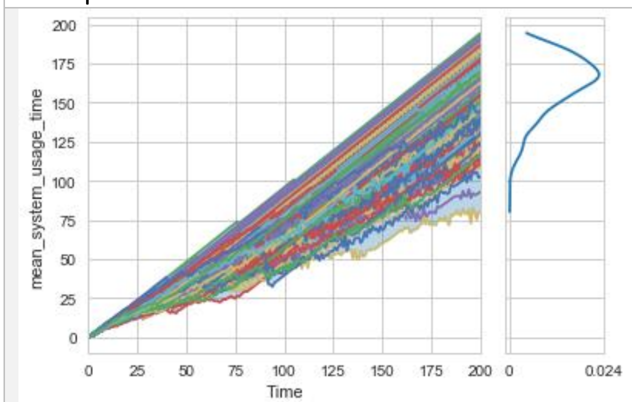
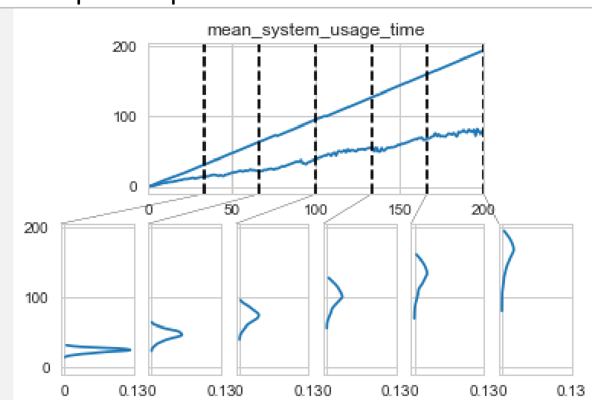
Lines plot	Multiple KDE plot
	

Table 65 Experimental outcomes - Experiment 2 – Mean system usage time

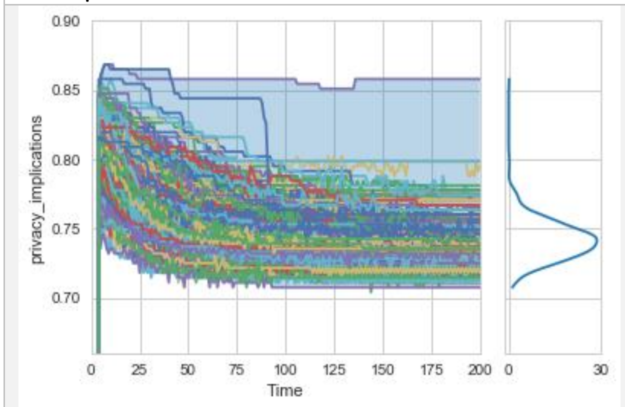
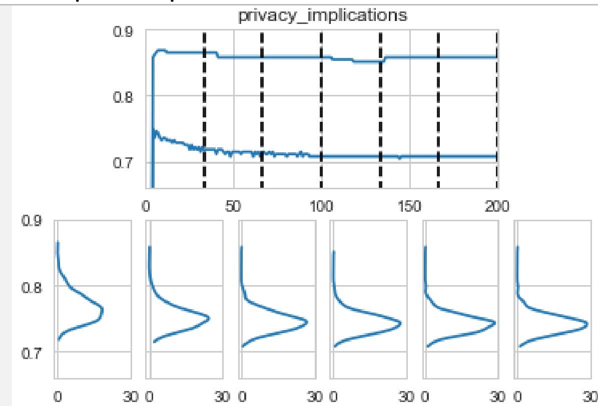
Lines plot	Multiple KDE plot
	

TABLE 66 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – PRIVACY SCORE

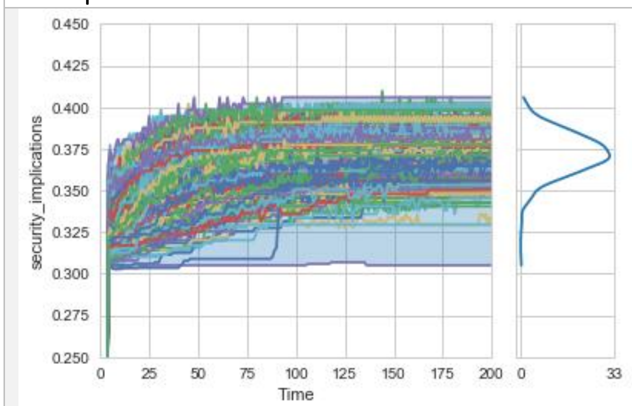
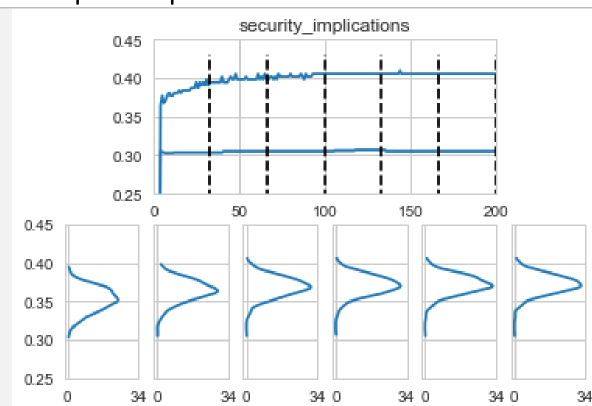
Lines plot	Multiple KDE plot
	

TABLE 67 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – SECURITY SCORE

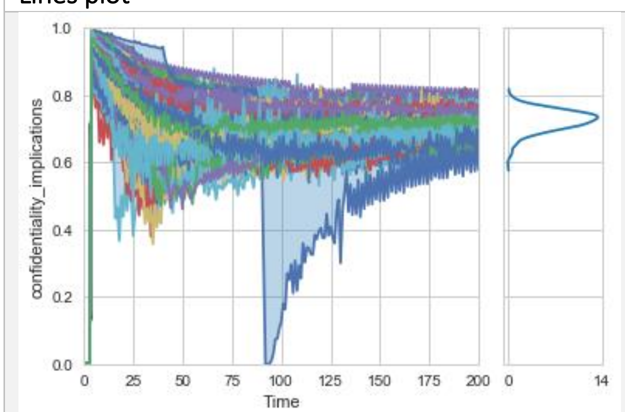
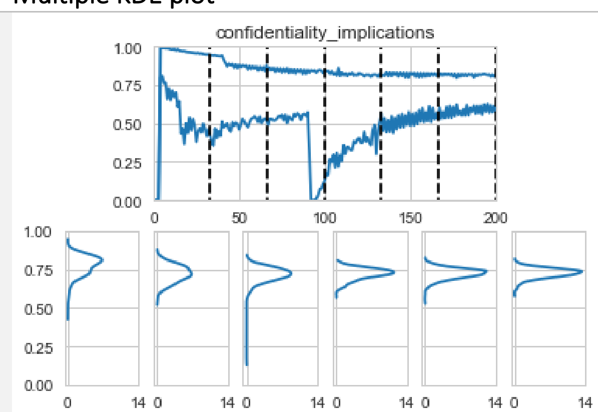
Lines plot	Multiple KDE plot
	

TABLE 68 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – CONFIDENTIALITY SCORE

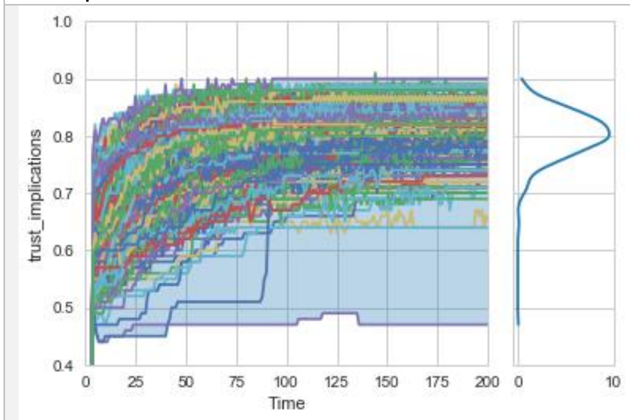
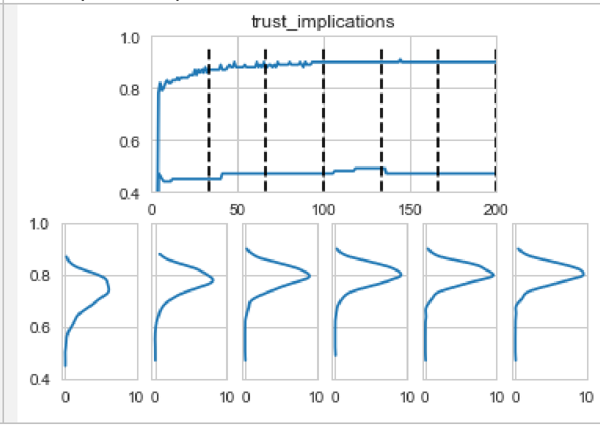
Lines plot	Multiple KDE plot
	

TABLE 69 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – TRUST SCORE

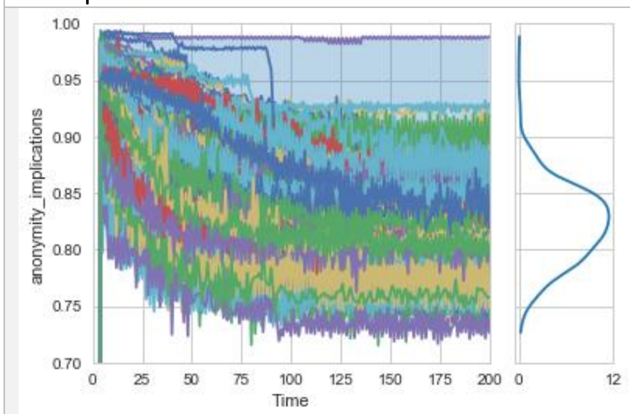
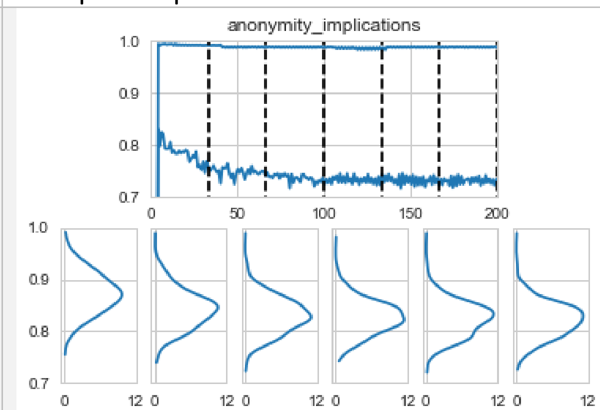
Lines plot	Multiple KDE plot
	

TABLE 70 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – ANONYMITY SCORE

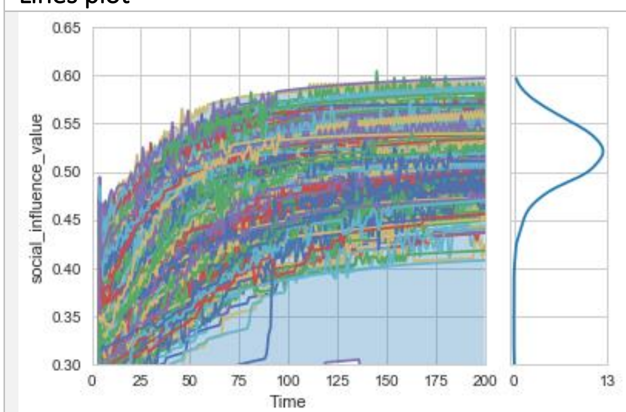
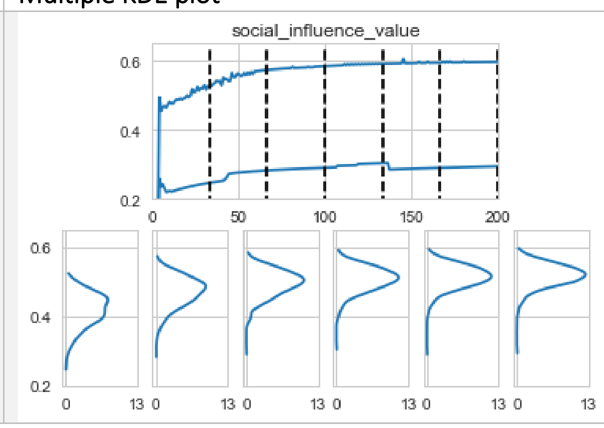
Lines plot	Multiple KDE plot
	

TABLE 71 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – SOCIAL INFLUENCE VALUE

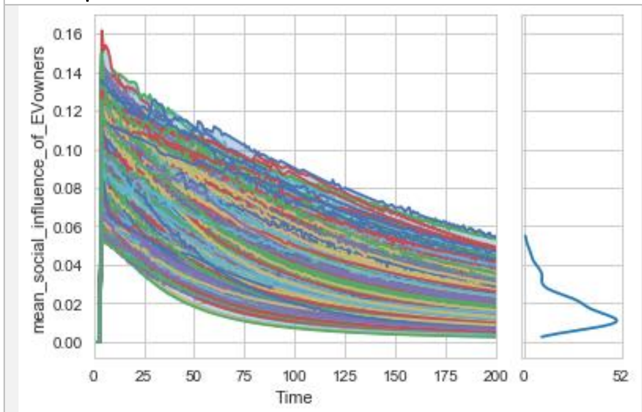
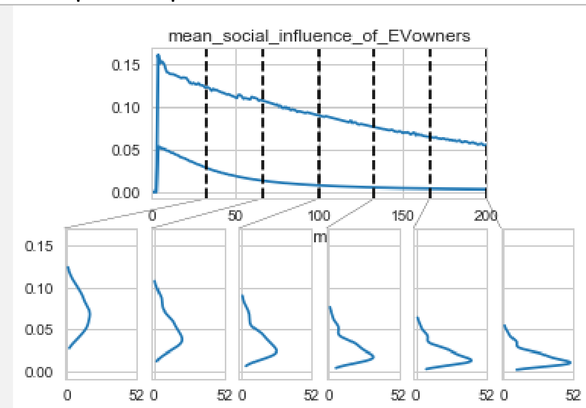
Lines plot	Multiple KDE plot
	

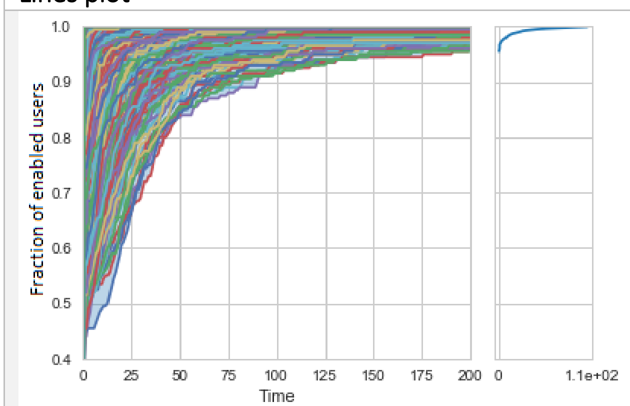
TABLE 72 EXPERIMENTAL OUTCOMES - EXPERIMENT 2 – MEAN SOCIAL INFLUENCE OF EV OWNERS

Appendix D.3: Design layout 3 experimentation data

Affinity	*Parameter*	*setting*
Standard model settings	*Level_of_decentralisation*	[decentralised]
	Data_storage_method	[on_chain_log_events]
	Blockchain_configuration	[private]
	Consensus_protocol	[proof_of_stake]
	Number_of_EV_owners	[200]
	Charging_pattern_spread	[0.5]
	Battery_range_spread	[50]
	Exp_network_effects	[2]
	Comparison_supply_PCP	[0.5]
EMA settings	Performance_threshold	[0.01 – 0.025]
	Effort_threshold	[-0.5 – 0.3]
	User_absence_compensation	[0.1 – 0.9]
	Min_skill_att_value	[0.05 – 0.2]
	Minimum_skill	[0.1 – 0.7]
	Skill_delinearisation_value	[0.1 – 0.5]
	Intelligence_distribution	[0.9 – 1]

TABLE 73 EXPERIMENTAL DESIGN LAYOUT 3 - PARAMETERS AND SETTINGS

Lines plot	Multiple KDE plot



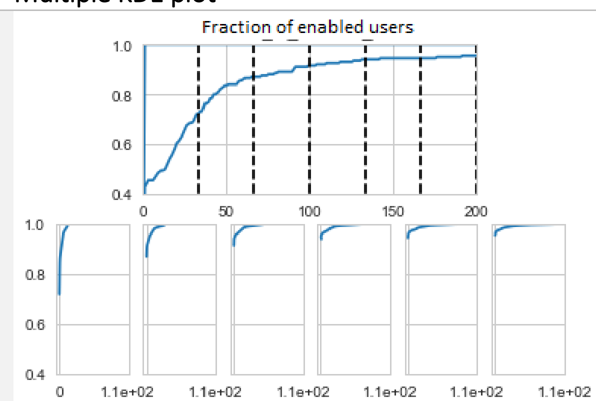


TABLE 74 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – FRACTION OF ENABLED USERS

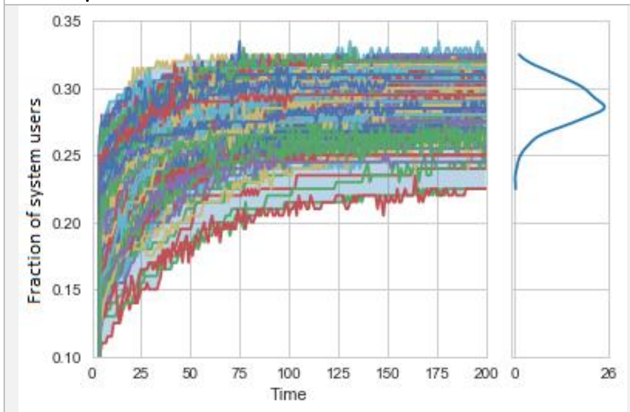
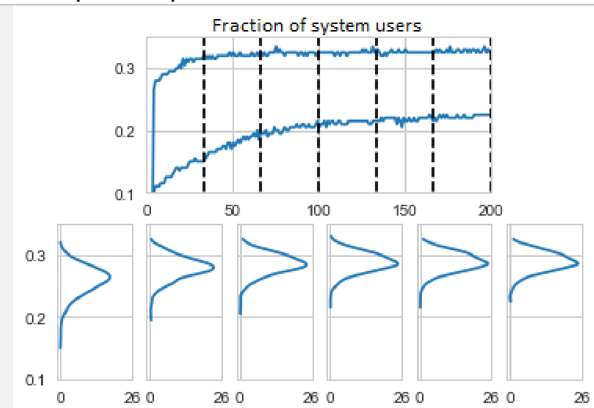
Lines plot	Multiple KDE plot
	

TABLE 75 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – FRACTION OF SYSTEM USERS

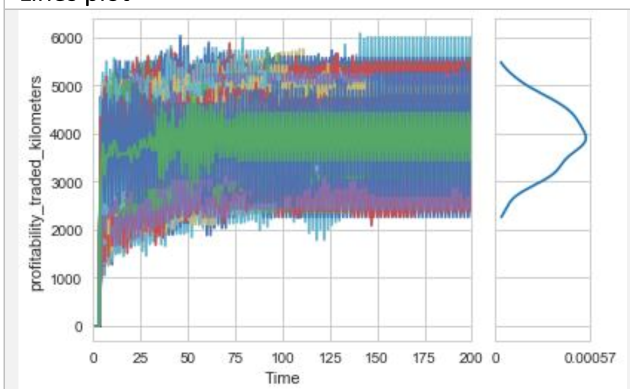
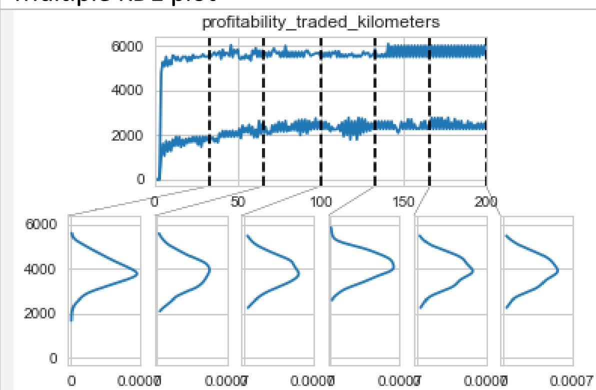
Lines plot	Multiple KDE plot
	

TABLE 76 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – PERFORMANCE TRADED KILOMETERS

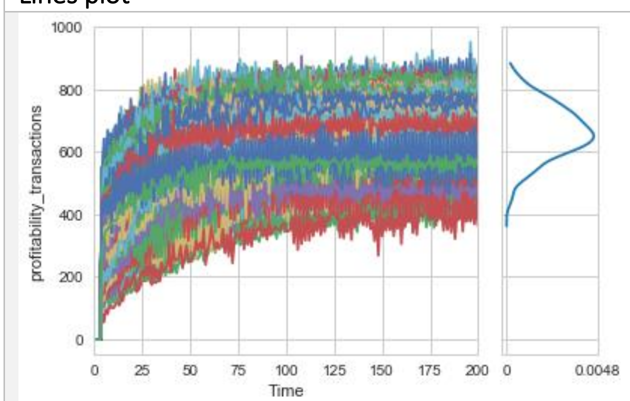
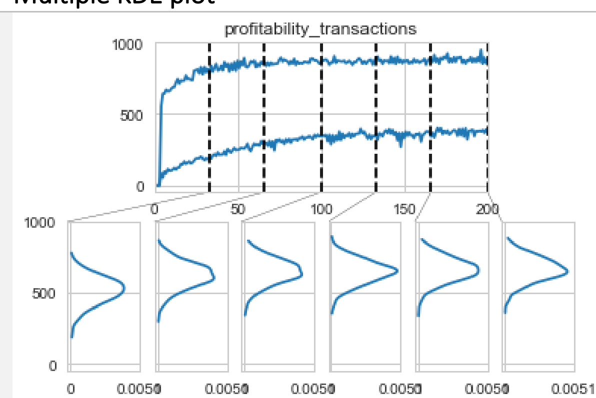
Lines plot	Multiple KDE plot
	

TABLE 77 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – PERFORMANCE TRANSACTIONS

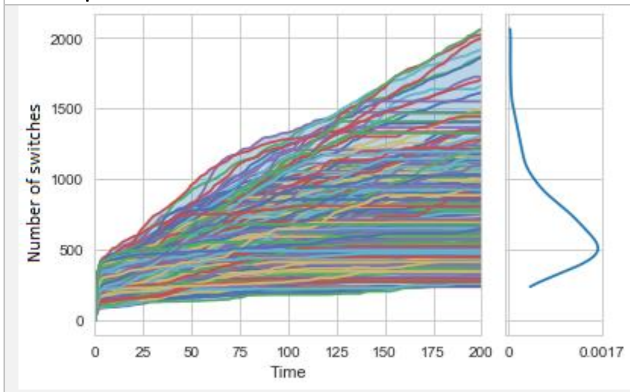
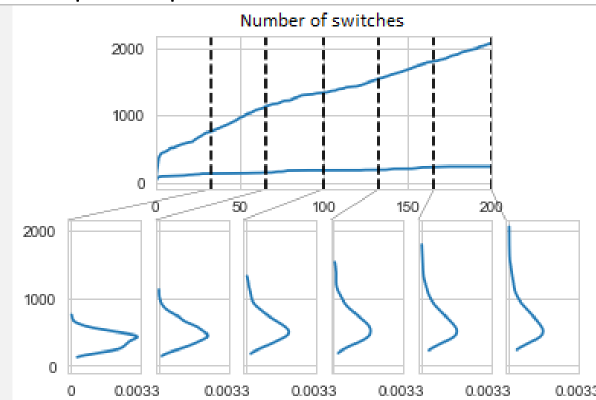
Lines plot	Multiple KDE plot
	

TABLE 78 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – NUMBER OF SWITCHES

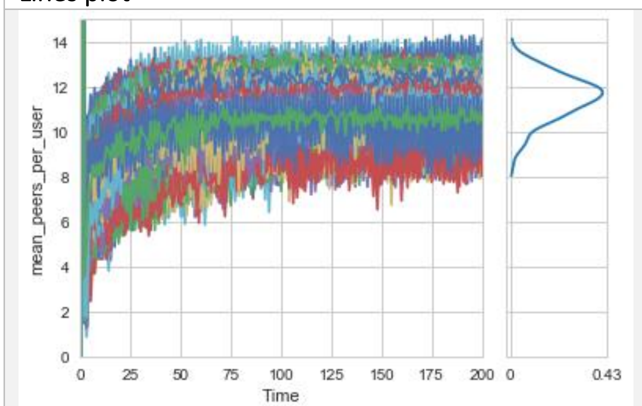
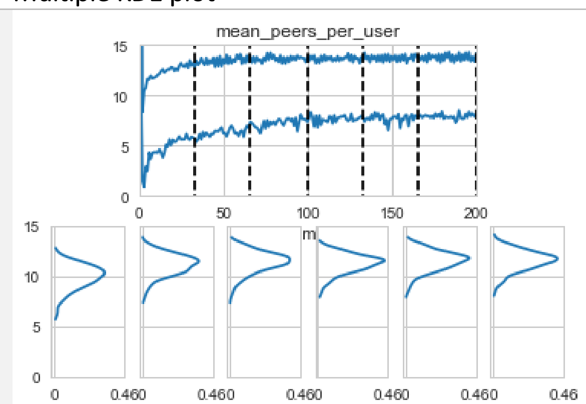
Lines plot	Multiple KDE plot
	

TABLE 79 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – MEAN PEERS PER USER

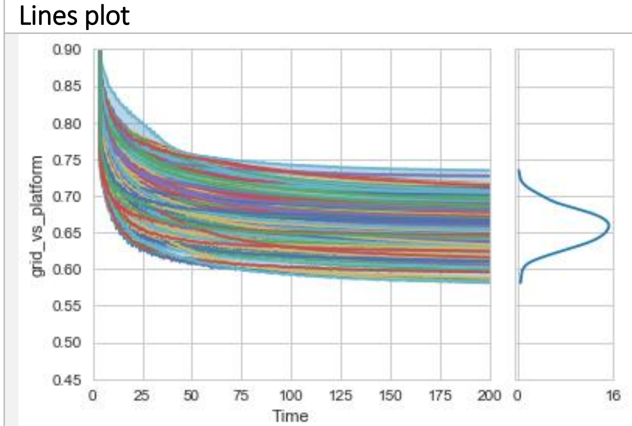
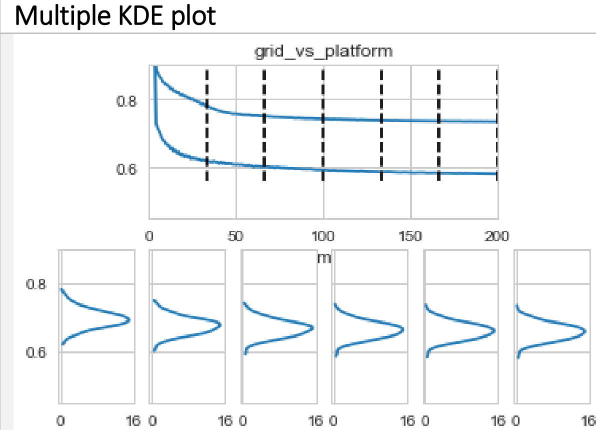
Lines plot	Multiple KDE plot
	

TABLE 80 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – GRID VERSUS PLATFORM

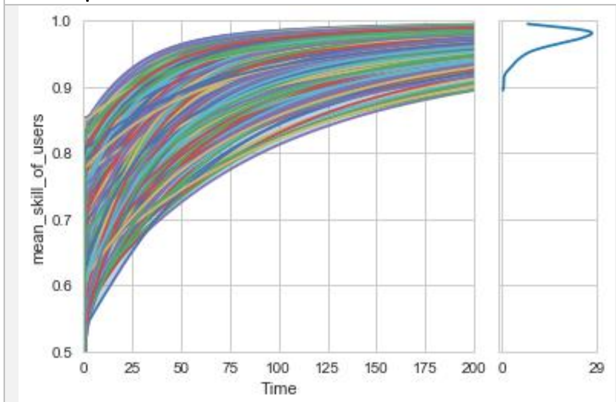
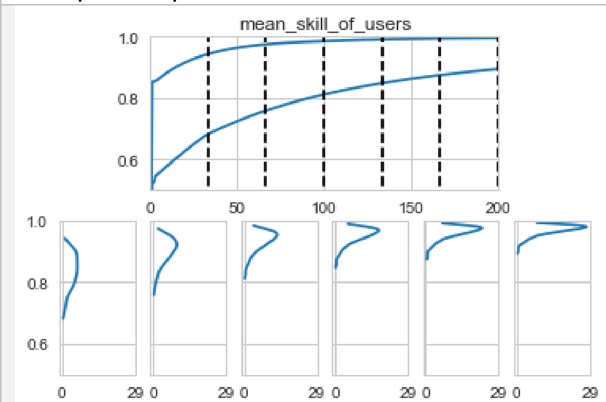
Lines plot	Multiple KDE plot
	

TABLE 81 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – MEAN SKILL OF USERS

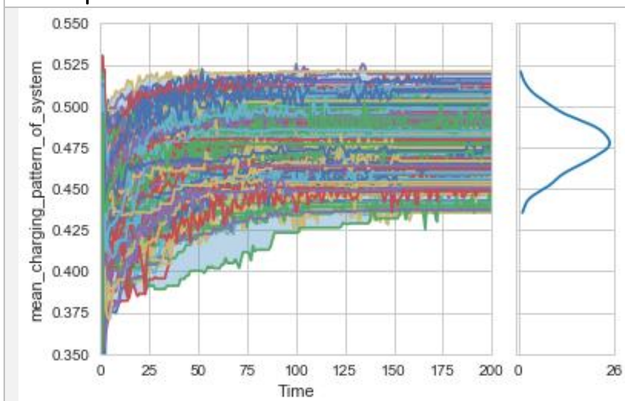
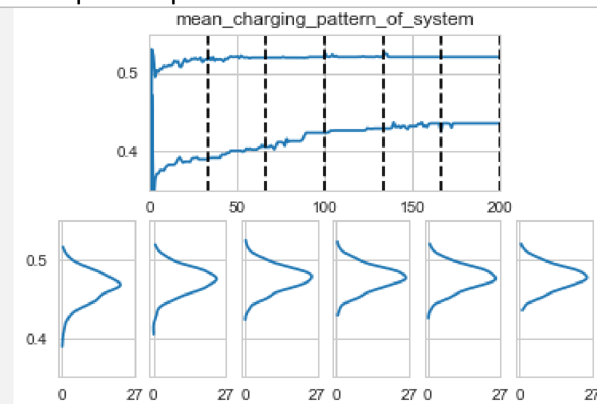
Lines plot	Multiple KDE plot
	

TABLE 82 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – MEAN CHARGING PATTERN OF SYSTEM

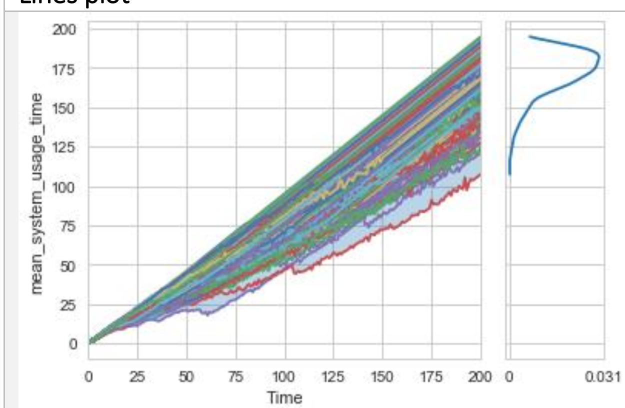
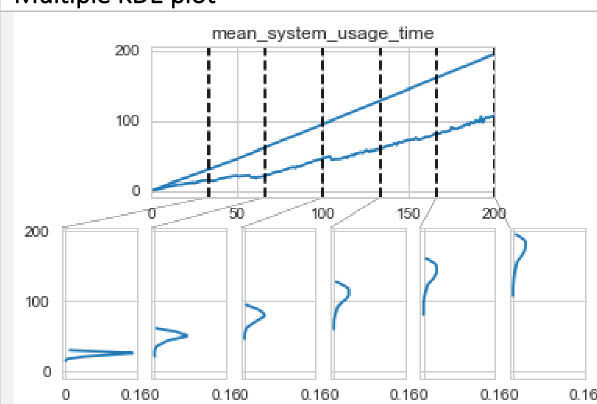
Lines plot	Multiple KDE plot
	

TABLE 83 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – MEAN SYSTEM USAGE TIME

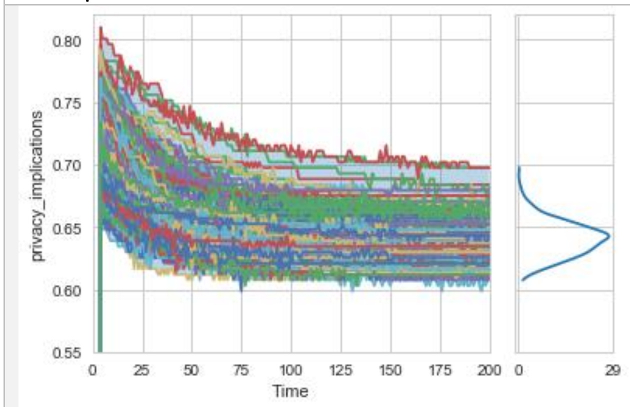
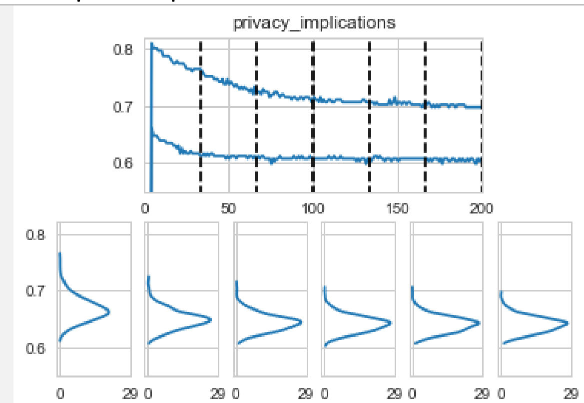
Lines plot	Multiple KDE plot
	

TABLE 84 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – PRIVACY SCORE

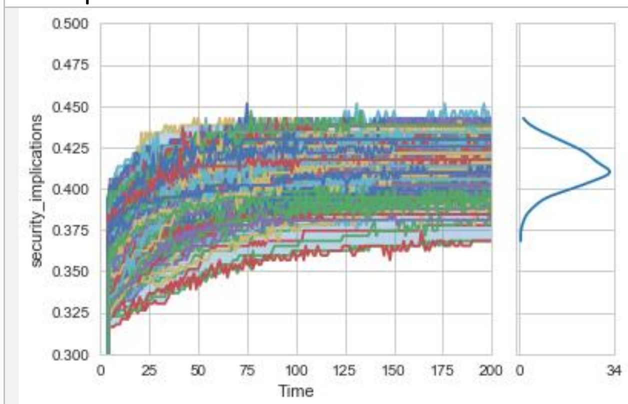
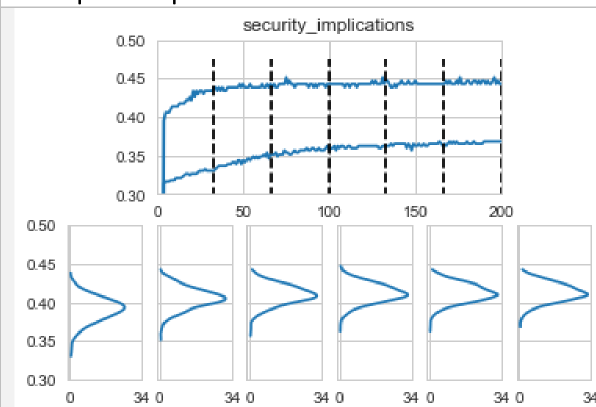
Lines plot	Multiple KDE plot
	

TABLE 85 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – SECURITY SCORE

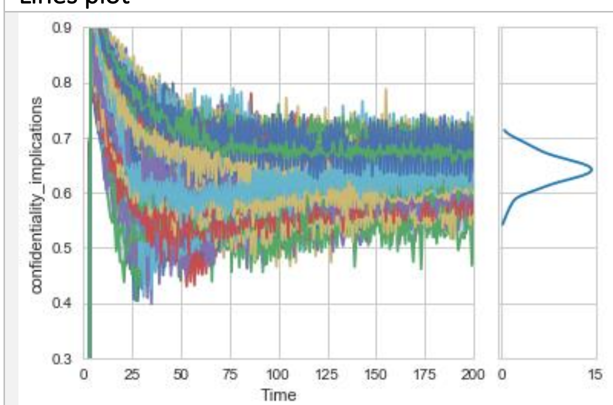
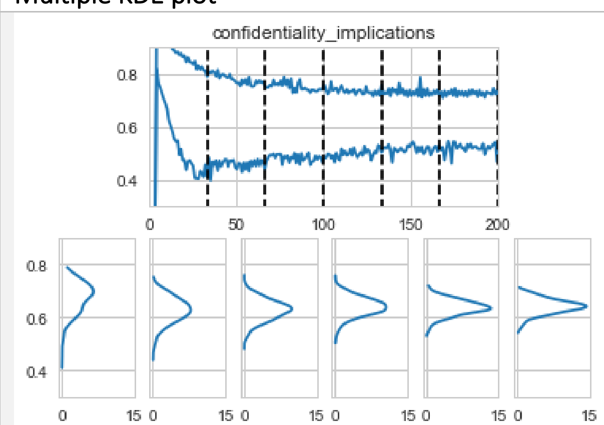
Lines plot	Multiple KDE plot
	

TABLE 86 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – CONFIDENTIALITY SCORE

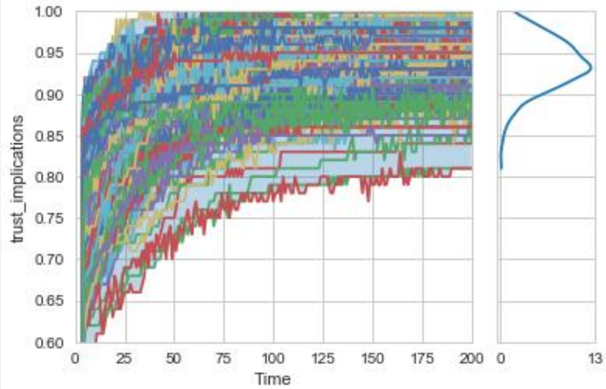
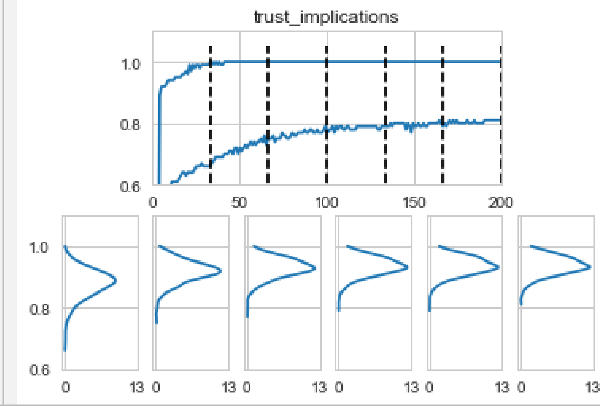
Lines plot	Multiple KDE plot
	

TABLE 87 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – TRUST SCORE

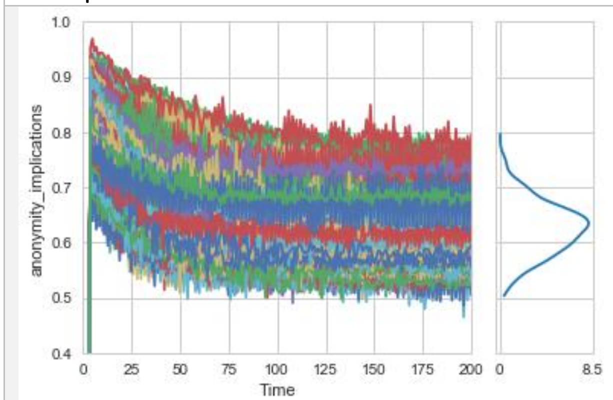
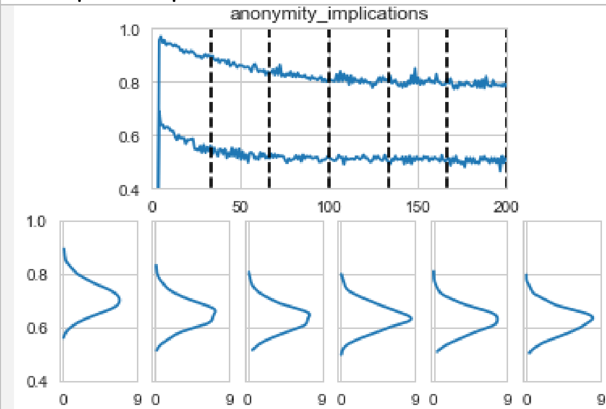
Lines plot	Multiple KDE plot
	

TABLE 88 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – ANONYMITY SCORE

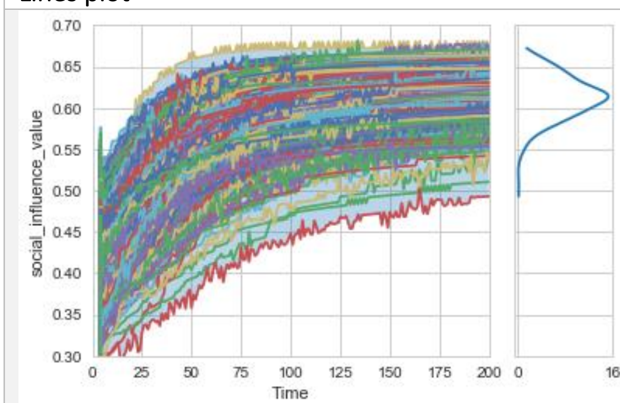
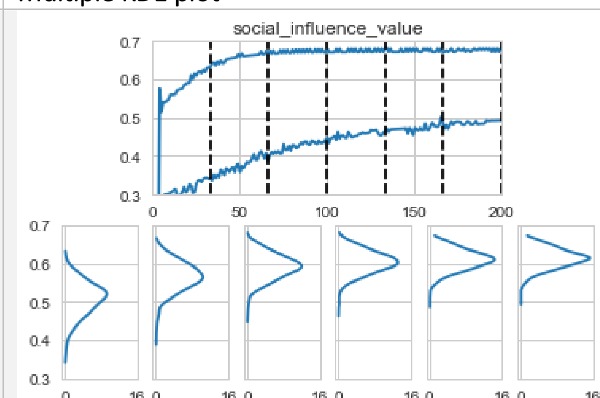
Lines plot	Multiple KDE plot
	

TABLE 89 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – SOCIAL INFLUENCE VALUE

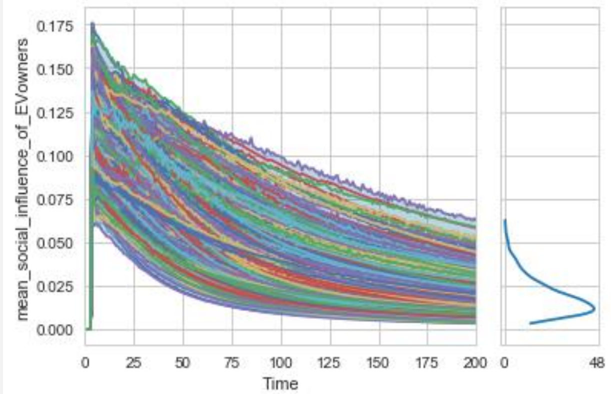
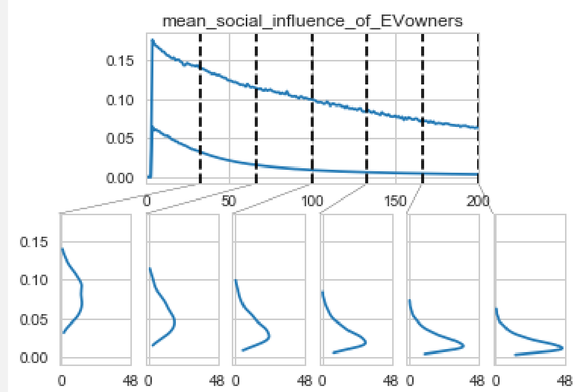
Lines plot	Multiple KDE plot
	

TABLE 90 EXPERIMENTAL OUTCOMES - EXPERIMENT 3 – MEAN SOCIAL INFLUENCE OF EV OWNERS