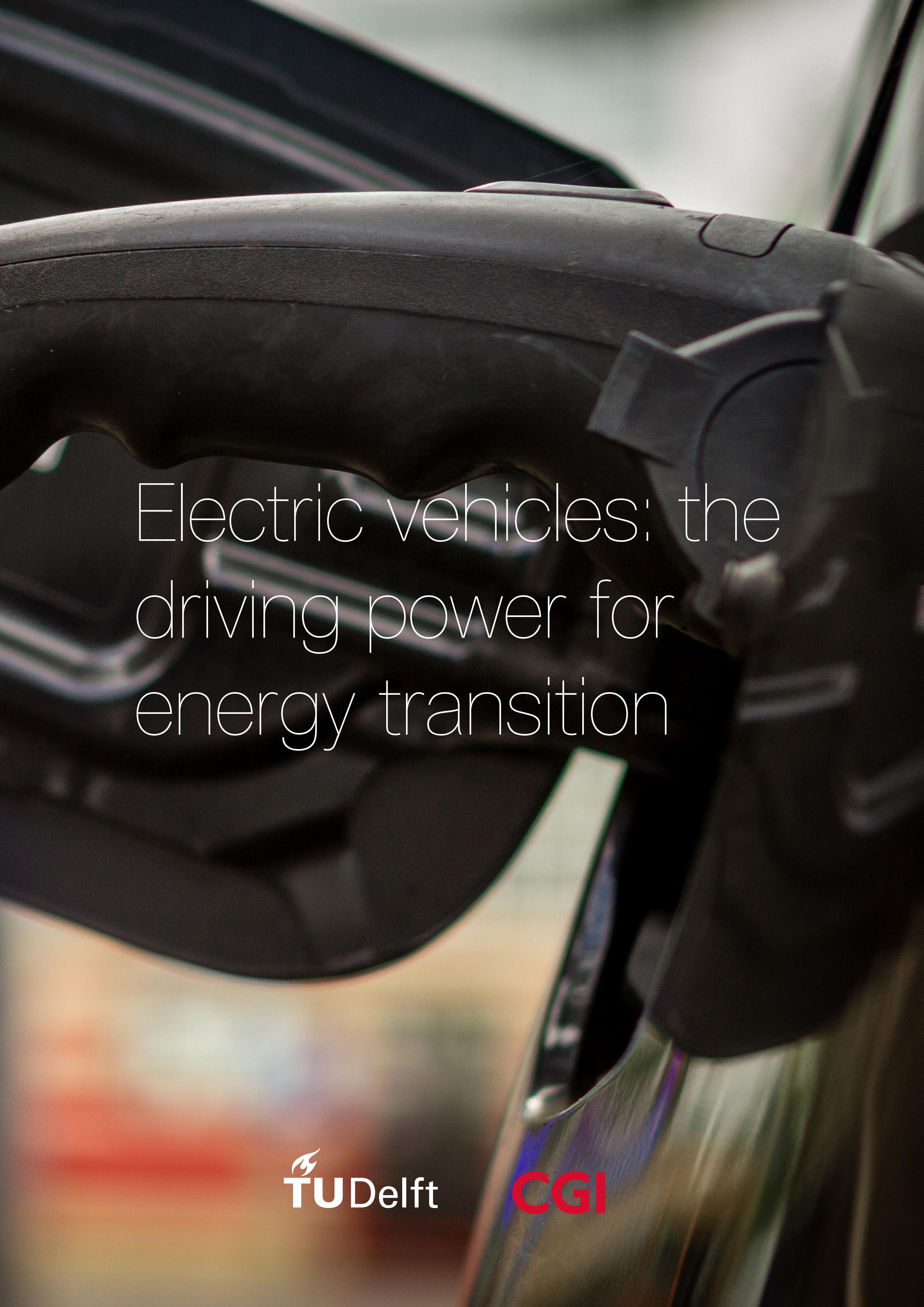

Electric vehicles: the driving power for energy transition


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Electric vehicles; the driving power for energy transition

Blockchain-based decentralised energy trading

by

S. Hijgenaar

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Wednesday April 26, 2017 at 11:00 AM.

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Preface

I feel truly proud to have worked on the energy systems of the future. The past 7 months having worked together with Delft University of Technology and CGI Nederland B.V. on smart grids and blockchain have been a thrilling ride. I am grateful to have been part of the “blockchain for utilities hype” from such an early stage and I thoroughly believe we will soon be beyond hype and developing the new status quo. As so many other of my life’s achievements, this project was a team effort and I would like to take this section to thank the following people.

First and foremost I would like to thank my first supervisor: Zeki. Your guidance has been so much more than I could have hoped for in a thesis supervisor. Our weekly sparring sessions gave me inspiration and motivation to exceed far beyond my own expectations. Thanks to you I have delivered a provisional conclusion to my academic career I can be genuinely proud of. Your PhD candidates Gamze, Majid and Chibuike took me in their office and sparked a cryptographic flame through their countless discussions, of which I am very grateful. Oguzhan, I even forgive you for stealing my spot. For everyone at the CybSec group I have forgotten: for making me fat an ugly through countless (Turkish) coffee and pie sessions I give you all minus ten.

I was very fortunate to have had such a diverse and wise committee. Alexander and Tamas, thanks to our inspirational meetings I got a sense of direction whenever I couldn’t find it. I am indebted to you for the extra time I got to take this project to new heights. Jos and Ralph (and everyone else at CGI), thank you for your support at every turn. Whatever I asked for was provided in the mere blink of an eye. With the help of the vast collected knowledge at CGI I was able to deliver something that can make an actual difference, rather than a good spot to put down your coffee.

Next, but very, very far from subservient: my lovely Yris. You were there for every up and down along the way, and stood by me through any stress-induced tantrum. Your constant optimism and perpetual energy pushed me to go on, even if I wanted to give up. I am lucky to have someone like you by my side, to count on and to have pleasant distractions with.

I would be nothing without a family. I feel privileged to have been able to go to university, for which I am 100% obliged to my lovely parents: Alex and Willy. Without your support this project wouldn’t even have been possible. I thank you for making me into the man I am today. Dick, I feel favoured to have a brother-from-another-mother with such a rich history. Never have your stories ceased to amaze me. I thank you for our morning swimming sessions, giving a refreshing kick-start to most of my thesis days. Our coffee sessions always inspired a creative new angle for my research, thank you.

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I thank you all.

S. Hijgenaar
Delft, April 2017

Summary

The Dutch energy system was designed from a central market-oriented perspective in a pre-renewable era. The consumption of small consumers is estimated by balance responsible parties, that aggregate over an area and place respective bids on the day-ahead market. The collective of bids and offers form a central market price for every hour of the next day. Estimation by balance responsible parties is done using assumption and generalisation, and therefore deviates from actual consumption. By law the market parties are required to partake in expensive intra-day trading to resolve the deviations. The severity of these localised imbalances is increasing as a result of the energy transition. The energy transition is characterised by a growing share of distributed resources as a result of rising concerns for the environment. Decentralised renewable energy generation and the rise of the electric vehicle cause highly unpredictable patterns of under and over supply.

This thesis aims to analyse the effects of electric vehicle charging on decentralised smart grids with a high penetration of renewable energy generation and the possibilities of using local trade to balance decentralised grids. A literature review is presented on the topics of the Dutch energy market and electric vehicle charging. In the status quo electric vehicles have adverse effects on power management, while their storage capacity could be used to locally balance out deviances between estimated and actual consumption. However, in the current situation, the Dutch energy market doesn't allow for local trading. A solution, based on blockchain, is presented that could facilitate decentralised electricity trade.

The name blockchain was given to the technology underpinning the popular cryptocurrency network Bitcoin in 2009. A blockchain essentially is a distributed ledger, containing an immutable record of transactions. In modern economies trade can only occur under the guidance of trusted third parties. These intermediaries become obsolete by using blockchain. Instead, trust becomes an autonomous product of cryptography and complex mathematics. By directly connecting selling and buying parties, trade becomes more efficient and quicker. A thorough analysis of blockchain's inner workings and consensus mechanisms is presented.

To analyse the electrical patterns that emerge in a smart grid environment, an agent-based model is developed, using smart metering data of a Dutch neighbourhood. By modelling a large number of individual agents subject to business logic, macro behaviour can be analysed. The model contains household agents and both public charging stations and household-owned pluggable electric vehicles. The emergent electricity patterns are used to analyse the imbalances occurring at decentralised grid level and the potential benefits of local trading can be analysed. As a proof-of-concept for blockchain-driven energy markets, the model's output is connected to a blockchain network.

It is found that local trade can help reduce the deviations between estimated and actual consumption and thus help balance decentralised smart grids. The positive effects increase with growing penetration of electric vehicles. The presented algorithm is effective at maintaining minimum state-of-charge at departure as well as keeping the charging session costs constant under fixed market tariffs. It is first of its kind to both incorporate large numbers of individual user preferences as well as benefit the system through peak shaving and shifting. Electric vehicle owners can expect to benefit financially by plugging in and offering their car as grid service provider. The results from the blockchain proof-of-concept, using the Tendermint platform, show that it is possible to securely store trade data on a blockchain, and consumers and grid operators can benefit from blockchain's immutability and transparency for e.g. billing. The proof-of-concept offers grid operators the first step towards safe local energy trade.

This thesis proposes a future work agenda that focusses on formalising blockchain as a technology for the utilities sector. From a business perspective, blockchain as a technology is still immature and can benefit from large market players offering standardised solutions. The proof-of-concept is a first step towards market acceptation. Ideas for possible model improvements are also given and tied to possible testing projects.

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1

Introduction

In The Netherlands, recent decades have seen the introduction of an energy transition: replacing fossil by renewables as primary source for energy generation. As is the case for most industrialised nations, the transition is fuelled by an increased awareness of our planet's liveability. Seeing the contribution of road traffic to the total amount of emissions in The Netherlands is roughly 10% [28], the potential benefits of an electrified automotive fleet are substantial.

The rise of electric vehicles and decentralised energy systems
The high popularity of electric vehicles (EVs), especially plug-in electric (PEVs) and plug-in hybrid electric (PHEVs) vehicles, of recent years is a result of the heightened concern for climate change and the advancements in battery technology. In The Netherlands the number of EVs has more than doubled in little under 1.5 years [145]. This trend is expected to continue world-wide as battery technology drives EV prices down and consumer comfort up, increasing the attractiveness of electric driving. For instance, the highly anticipated Tesla Model 3, due fall 2017, was reserved almost 400,000 times within 2 weeks world-wide [63] of which an estimated 20,000 can be attributed to The Netherlands [171].[49] show in their work on the impact of EV usage in Lisbon that the use of EVs in urban regions can result in a significant drop in emission of harmful gasses.

Besides the increased use of EVs another trend that is linked to the energy transition is the increase in decentralised power generation. Through offering subsidiaries to home owners, like the ISDE [146], and/or companies, e.g. the SDE+ [147], local and central governments try to encourage home and business owners to invest in sustainable decentralised power generation. As a result, the energy transition does not only entail the replacement of fossil by renewable energy carriers, but also a shift from central to decentralised power systems.

EVs and green, decentralised energy generation can become important keys to unlocking future sustainable energy systems. However, their introduction leads to several new problems. According to [76] power systems driven by renewable generation face a number of problems, owing to its intermittent nature. Problems may include, amongst others, voltage fluctuations, surges, and frequency variability, resulting in low reliability and quality. According to [195] the increase of distributed generation (DG) can lead to situations where the market price no longer follows the market demand. On the demand side, "uncontrolled charging" may lead to demand peaks, making the technology hard to coincide with a variable power source such as wind or the sun [158]. Furthermore, it increases already existing peak load. Problems are caused on a decentralised level, while the centralised market model is designed to solve them from a central point-of-view.

The variable nature of renewable energy generation (REG) on the one side and uncertain PEV demand on the other, leads to increasing problems for the transmission system operator (TSO) (TenneT in the case of The Netherlands). As the penetration of both technologies increases, which it is expected to do, these problems will rise to levels at which balancing is no longer possible on a central scale and critical failures may occur. A possible solution involves reallocating balancing responsibilities from a central to a decentralised level. This introduces the concept of smart (micro)grids. Zones, be it residential, industrial, or a combination, with a potential for local energy net balance, in literature known as islanding [47]. However, if introduced into the current centrally-orientated control paradigm, the large number of newly introduced actors would tremendously increase system complexity. Moreover, the central markets offer little transparency and guarantees of (data) security to household consumers [16, 130, 151–153]. The prosumer movement would draw more and more system responsibilities to the household level, resulting in a transition not only from grey to green and central to decentralised, but also from top-down to bottom-up. However, this transition requires a new platform that can increase distributed influence in the power system, while maintaining system security and increasing transparency. A technology on which such a platform could be based is blockchain.

Blockchain, the technology behind Bitcoin

In 2008 Satoshi Nakamoto published his/her/their paper on a new type of payment system: Bitcoin: A Peer-to-Peer Electronic Cash System [121]. With Bitcoin, the first true application of what is now called blockchain technology was fact. In 2009 Nakamoto launched the first Bitcoin software as an open-source, fully distributed and decentralised tool to host the world's first ever peer-to-peer electronic payment system [123]. Essentially, this entails that everyone has full disclosure of a public ledger, i.e. the complete transaction log, and the software is not in hand of one single entity, be it individual or collective. Moreover, the software is freely open to everyone who wants it, granting freedom of application. Bitcoin was the first ever practical realisation of direct transactions without the need for a trusted third party (TTP), allowing transparency, speed and flexibility. Ownership and value is proven through complex cryptography rather than a central minting authority.

There is no widely acclaimed evidence from academia that blockchain technology could in fact facilitate energy markets, but the application of Bitcoins or blockchain-based technology is not a complete novelty in the energy/utilities sector. SolarCoin is a cryptocurrency, similar to Bitcoin, that is awarded for every solar-generated MWh that is fed to the grid [169, 183]. A South African start-up, Bankymoon, is enabling the purchase of pre-paid electricity using Bitcoins as currency. Using smart meters Bankymoon wants to facilitate sending energy anywhere over the world, e.g. donating utilities to underprivileged schools in Africa. The technology is expected to stop electricity price inflation, increase transparency and make affordable electricity available to everyone, regardless of accessibility to centrally offered services such as a bank account [23, 108, 115, 137]. Grid Singularity wants to enable blockchain-based energy trading in developing countries [70, 97]. Power Ledger is an Australian company that offers automated energy trading through blockchain technology [128, 134]. Seeing the proof-of-work [121] concept of Bitcoin's crypto mechanism imposes a significant energy consumption, Power Ledger relies on the concept of proof-of-stake [87, 135]. A similar initiative in Brooklyn (New York city) called TransActive Grid/Brooklyn Microgrid facilitates peer-to-peer energy transacting in a street-wide microgrid using blockchain [43, 136, 154, 157, 184]. The network runs on smart contracts, programmed using the Ethereum code-base [100]. Electron is an UK-based company that aims to deliver energy market functionality through smart contracts, broadcast through a public blockchain ledger. Their goal is to facilitate all 53 million supply points in The UK [51, 52]. In Germany, RWE, one of the biggest players on the energy market, together with Slock.It have started a pilot project on blockchain-based EV charging. The developed prototype creates smart contracts between the EV (owner) and the charging station, that acts on behalf of RWE. By employing smart contracts and blockchain the transacted units can be very small, allowing for precise purchases rather than paying by the hour [4, 48].

Research statement

The purpose of this research is to investigate how electric vehicles can aid in the decentralisation of traditional power systems. The aim is to show that electric vehicles can complement and, in the long run, replace centrally-driven services for regional sub-systems. Furthermore, the usefulness of blockchain technology for the electricity market is analysed. Using blockchain to promote energy trading between PEV owners and other system users can be seen as a convenient starting point. Namely, PEVs are already heavily reliant on computer systems and therefore offer an easy testing implementation base. With the slow, but steady roll out of smart meters and advancements in internet of things (IoT) technology, the results from this study will prove blockchain's worthwhile for the smart grids of the future. The main research question of this thesis is

How can electric vehicles promote energy transition and how can blockchain facilitate the decentralisation of future energy systems?

This research question will be broken up further by the following sub-questions:

- How could (sub-)systems in the power grid benefit from a fleet of electric vehicles?
- What is blockchain and how can it facilitate decentralised utilities?
- What are likely scenarios for future energy systems and how will they affect peer-to-peer trading?

- What are criteria for implementing blockchain into smart (micro)grids?

Methodology
The analysis will be based on an agent-based model of a smart grid. The model will use smart metering data collected from 6-9-2011 through 31-8-2014 of a Dutch neighbourhood. The dataset contains quarterly consumption data, collected from of a few hundred households. Using electricity profiles as an indicator of forecasted demand, the BRP's need for intra-day market trading can be calculated. The goal is to see to what extent PEVs can help reduce this under variable penetrations of REG and how large the transactional throughput will be under varying circumstances. Therefore, two scenarios of the energy transition were developed:

- 2025: The trends in battery technology are assumed to lead to a short-term future where fully electric, or battery electric vehicles (BEVs), have overtaken PHEVs in number. Accordingly, the number of public charging stations will increase as well. As a result of the introduction of Tesla's Model 3 and other car manufacturers plans to release low-budget, high-radius BEVs, the penetration rate of PEVs is expected to go to 25%, with an BEV share of 80%.
- 2035: The Dutch government has plans to ban the sales of cars with internal combustion engines (ICEs). The Minister of Economic Affairs wants, per the Energieakkoord (energy agreement), to force all cars sold from 2035 to be able to operate in CO_2-neutral mode. The Dutch state wants to solely allow the sales of BEVs by 2025. Based on these policies and in accordance with CGI experts the share of PEVs is estimated to be 80%. The share of BEVs is expected to grow on to 90%.

The model's output will serve as indicators for blockchain performance requirements. A blockchain design is proposed based on the Tendermint platform. The technology will serve as an aggregator, allowing BRPs to be cut out in favour of autonomous trading on the markets. The network is offered as a proof-of-concept for blockchain-driven, local energy markets.

Thesis structure
The outline of this thesis is as follows. In Chapter 2 important aspects of electric vehicles in combination with decentralised power grids are discussed: through a literature study important opportunities and possible pitfalls of EV charging in a smart grid context are presented. In Chapter 3 the concept of blockchain is presented and different consensus models are explained. Chapter 4 gives a more thorough explanation of the analysed scenarios and the model's structure. Next, Chapter 5 presents the results from the simulations and their implications for blockchain design. The discussion of results and opportunities for further development and research will be conferred in Chapter 6. Finally, concluding remarks will be given in Chapter 7.

2

Background on electric vehicles and the energy transition

Over the last decades, energy systems in The Netherlands have undergone several transformations. In the 1998 Electricity Act, the Dutch market was opened up for free competition and with the 21st century came the wide-spread adoption of electrically powered cars. Furthermore, as the global awareness for the enhanced greenhouse effect increased, so did the transition towards sustainable energy generation by public and private actors. A growing part of this generation is coming from decentralised units, for instance non-energy businesses and home-owners. Much has happened since 1998 and the institutional framework set in place then, may well no longer fit the current technological standards and consumer roles. Therefore, this chapter gives a review of the current state of affairs concerning the Dutch energy system, as well as the effects of plug-in electric vehicles (PEV) on decentralised power grids. The outline of this chapter is as follows. Aspects of the liberalisation and decentralisation of the Dutch energy market are presented in Section 2.1. Following is an analysis of the effects that charging of PEVs has on power management in Section 2.2.

2.1. Energy transition in the Netherlands

Since the 1998 Electricity Act, the Dutch energy system has been characterised by liberalisation and unbundling. As a result, we went from vertically integrated, local monopolies to an open market with a clear separation between different aspects of the value chain. However, the transformation of the Dutch energy framework didn't stop there. Following trends in sustainability and technology, our energy markets are subject to continuous change. The dynamics resulting from an increase in the number of market operators cause uncertainty in power management and require smarter control solutions. This section serves as an introduction to the institutional framework of the Dutch power system, starting with a short history of the liberalisation in 2.1.1. In 2.1.2 the implications of the decentralisation of the power system are discussed. Finally, this section concludes with an analysis of important ancillary services for liberalised energy markets.

2.1.1. Liberalisation and unbundling of the energy market

Before the liberalisation imposed by the 1998 Electricity Act, the Dutch power market was an oligopoly. Under heavy regulation by the state, several publicly owned regional energy companies provided everything from production to distribution and metering. A utility service provider (USP) was selected solely based on where consumers resided. While the system was said to be cheap and effective, there was little incentive for (system) efficiency [8]. As a result of the 1989 Electricity Act the market had opened up for smaller, decentralised generation units, incentivised through a feed-in tariff based on system peak price. As the supply from decentralised units (mostly combined heat power (CHP)) rose, the demand from centralised units decreased, in turn increasing the system peak price [91, 191]. As the market share of decentralised generation increased, so did overcapacity.

Because of this market inefficiency, the Dutch government enacted the 1998 Electricity Act and moved to liberalise the energy market. Besides the national agenda, liberalisation was also part of European Union laws [191]. In the period of 1998 to 2004 the Dutch energy market was opened up in phases, starting with free choice of supplier for the largest consumers, then the medium consumers and finally the small (household) consumers in 2004. The 1998 Electricity Act not only gave accordance to the European decree for free competition, but also for the unbundling of utility companies. Thus, no one legal entity could be active in multiple sectors of the value chain, for instance generation and distribution. Due to being a natural monopoly, transmission remained state-owned through the transmission system operator (TSO) TenneT. Furthermore, to safeguard network quality and a high service level for consumers, distribution came under state regulation in distribution grid operators (DGOs). As opposed to these two sectors, generation and retail operate under the principles of free competition. Generation units were no longer bound to capacity thresholds and as a result of the new market mechanisms everyone received a fair price for every unit of electricity. Starting from 2004, home owners were completely free to choose a utility provider to their liking. Figure 2.1 shows the energy market structure as a result of the 1998 Electricity Act.

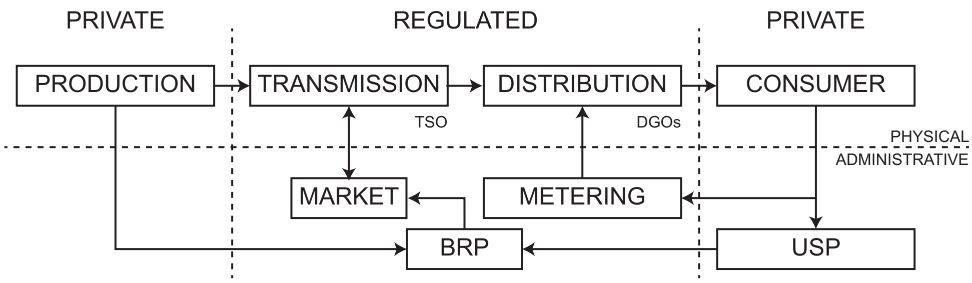


Figure 2.1: A graphical representation of the Dutch liberalised electricity market structure after 1998

Very large consumers, for instance industrial sites, have a high, relatively constant demand. Accordingly, they can reach long-term agreements with their preferred suppliers through multiyear contracts. Other consumers operate, or are represented, on electricity markets. On the market, balance responsible parties (BRPs) are tasked with maintaining balance of supply and demand. Producers make an estimation of their production and place an offer for a certain price per unit of electricity. On the demand side, BRPs place bids to buy an amount of energy as a large consumer or as aggregator for a number of medium and small consumers. Figure 2.2 shows an example of a resulting curve on the Amsterdam power exchange (APX) day-ahead market. The day-ahead market is one of the available markets in the Netherlands, the other being the intra-day, or spot, market. On the day-ahead market BRPs place their bids (before noon) for every hour of the subsequent day. On the intra-day market BRPs can trade with a minimum of five minutes dispatch time. This provides the parties with a last-minute resort to resolve any imbalances [7]. Prices on the spot market are generally higher than those of the day-ahead market. The reason being that TenneT will penalise any BRP that deviates from placed bids, which would result in grid imbalances [131].

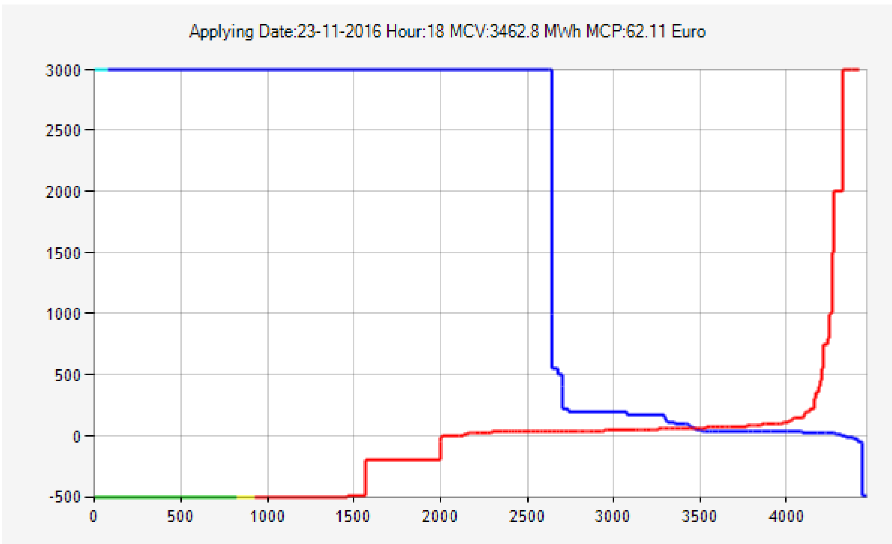


Figure 2.2: Aggregated curve of the day-ahead market (APX) on the 23rd of November 2016 for the 18th hour

The energy transition is the movement from fossil fuels to renewables as the primary source for energy generation. [193] state that the Dutch government has been active in the development of a more sustainable electricity system. However, the share of green energy is still far from that of other European countries. As a result of the oil crises and outages in the second half of the 20^{th} century, the Dutch government made certainty of supply and fuel diversification top priorities. Measures initiated by the first two energy whitepapers and the 1989 Electricity Act pushed the system towards a higher share of CHP, rather than towards a more sustainable generation profile. As a consequence of the top-down view of the Dutch government, subsidies and other incentives for green energy were often aimed at large-scale integration of renewables, such as wind energy and biomass, into the existing power scheme. These projects were often found to be too ambitious or lacked public support [193].

Although policy by the Dutch government, including the liberalisation act from 1998, didn't lead to the desired penetration rate of renewables, it did start a decentralisation of the energy system. With technological advances came a bigger interest in distributed renewable energy resources by small consumers, such as rooftop solar panels. In turn, consumers changed in prosumers.

2.1.2. Distributed generation

Following the liberalisation that took place from 1998 to 2004, utility providers are required to offer a fair price for every unit of power that is fed back to the grid. On top of that, Dutch policies favoured power quality through securing supply certainty and diversifying generation types. This has lead to an increase in distributed generation (DG) [78]. Accoring to [1] "DG is an electric power source connected directly to the distribution network or on the customer side of the meter." With every increase in DG the power systems moves away from a centrally-oriented, top-down energy system to a decentralised, bottom-up one. Thus, DG is an important factor in the energy transition.

Another concept that is strongly linked to the energy transition is smart grid. A smart grid is a decentralised power grid that relies on two-way communications in the entirety of the system to facilitate efficient use of available resources [66]. The smartification of the energy system is key to guide the process of decentralisation [62].

Numerous benefits are credited to DG. Amongst others, systems could benefit from a higher penetration of renewable energy generation [174]. Seeing the relatively high share of CHP in The Netherlands, the power system could benefit from efficiency upgrades through DG [3, 72]. Moreover, as DG is attached directly to the distribution grids, close to consumption, investments in transmission and distribution can be substantially decreased [114], as well as avoiding transmission losses [35]. Furthermore, (smart) grids with a high degree of DG have the potential to provide certainty of supply in case of grid outages, as DG offers flexibility and locality [12].

However, DG doesn't come without it's downsides. According to [47] decentralised grids with a high penetration of DG can lead to problems for operational reliability. Intermittent power sources can cause power harmonics and reverse power flows and thus require more voltage regulation. These ancillary services are described below. To effectively integrate DG into distribution networks without storage capacity [79], and thus contribute to a more efficient and sustainable power grid, active network management is required [104].

2.1.3. Ancillary services

According to [90] "[a]ncillary services are those services provided by generation, transmission and control equipment which are necessary to support the transmission of electric power from producer to purchaser. These services are required to ensure that the [s]ystem [o]perator meets its responsibilities in relation to the safe, secure and reliable operation of the interconnected power system." One of those services is frequency control. According to [127] storage capacity is essential for stabilising frequency in energy systems that face a high penetration of RESs. Because of the intermittent nature of RESs, the most important criterion for ancillary services relates to the speed at which they can react to prevailing network changes, also called deployment times. [140] identify three types:

1. *Deployment start*, the time from request signal to response;
2. *Full availability*, the time from reception of the signal to end of ramp-up;
3. *Deployment end*, the maximum duration time of the service provided.

In The Netherlands the deployment start of the primary reserve is zero, the full availability 30 seconds and deployment end 15 minutes [65]. According to [140] the most important ancillary services deal with frequency control or voltage control.

Frequency control
Frequency control is used to balance load and generation. Imbalances between load and generation might be a result of short-term load variations, errors in predicting load or schedule changes [65]. Frequency control is split into primary, secondary and tertiary control, or reserve [139, 140]:

1. *Primary reserve* is used for quick, immediate responses to local network fluctuations. It is used to balance out the active power generation in case of e.g. large generation or load outages
2. *Secondary reserve* is exerted centrally and balances network fluctuations between different local networks. Effectively, the secondary reserve makes sure that frequencies return to nominal levels after primary control has stopped the exacerbation of imbalances
3. *Tertiary reserve* is then finally used to replenish primary and secondary reserves

In distributed systems the frequency deviations are larger than those in centralised ones. Respectively, these systems can benefit the most from quick-response primary frequency control [140]. Storage capacity is an important tool for matching generation and load times and offer frequency control. The electrification of the automotive fleet has the potential to provide this storage capacity. However, the low maximum output of most PEV grid connections requires aggregators: actors that cluster and manage a large number of PEVs and thus reaching the desirable/required economies of scale [139]. Consequently, the aggregators need to account for a wide variety of user preferences, and the principal difficulty arises from central control requirements and decentralised impact on consumers [65]. This discrepancy often leads to difficult control strategies, imposing complicated prediction models and optimisation problems. The design in Chapter 5 tries to avoid these problems by lowering generalised transactions costs and facilitating a transactional framework for one-on-one ancillary service trading and autonomous frequency control.

Voltage control
There is a close relationship between voltage and reactive power control, i.e. all service providers must either produce or absorb reactive power. Like frequency control, voltage control is separated into primary, secondary and tertiary control. This entails local automatic, centralised automatic, respectively manual optimisation of reactive power flows [140].

Economics of ancillary services
The TSO usually buys ancillary services from generators and consumers. There are four markets the TSO can turn to [141]:

1. *Compulsory* provision is imposed to large generators as a part of their contractual grid connection. Criteria for compulsory provision are often simplified, resulting in unfair cost allocation over service providers. Compulsory provision is often used for basic voltage control;
2. *Bilateral contracts* are contracts with a preset quantity, quality and price, resulting in agreements that are better tailored to specific situations and services. Bilateral contracts are often complex, costly, impose high transaction costs and lack transparency. Bilateral contracts are primarily used for primary frequency control and voltage control;
3. *Tendering* and *spot markets* are both used for closing short-term contracts, where standardised services are traded on spot markets and tendering is used for less standardised services. Tendering is most often used for primary frequency control and enhanced voltage control, while spot markets are only used for frequency control. According to [139] in the Continental Europe system (ENTSO-E CE/UCTE) all frequency control is tendered by the TSO.

On these markets three different price signals can be used [141]:

1. *Regulated price*, which is a pre-defined price, equal for all players. This generally results in economically sub-optimal situations;
2. *Bid systems*, which result in prices based on accepted offers. Bid systems are often used for services with fluctuating quality (requirements). This system is the most widely applied over all ancillary services;

3. *Common clearing price*, which leads to prices based on the highest accepted offer or the least expensive rejected offer. These systems lead to economically optimal prices for homogeneous products.

2.2. Plug-in electric vehicles and power management

As mentioned in the introduction of this report, a significant proportion of harmful gas emissions originate from the automotive sector. As a result, the interest in electric vehicles (EV) has grown substantially over recent years. This sections aims to analyse the beneficial and adverse effects that EV charging can have on power management. Logically, only those EVs with a possible connection to the grid, i.e. plug-in electric vehicles (PEVs), are considered. In Section 2.2.1 the effect of PEVs on system load patterns is considered. In 2.2.2 the potential of the battery capacity of a fleet of PEVs for power management is studied. Finally, the Dutch situation, in terms of penetration rate, car model distribution and battery characteristics, and mobility patterns, is presented in 2.2.3.

2.2.1. Effects of charging on load balancing

Moving from conventional internal combustion engines (ICEs) to electrical drive vehicles can have substantial benefits for the environment. PEVs recharge at charging stations using electricity that has been generated with a much higher efficiency than most ICEs. Moreover, if the consumed electricity comes from renewable energy sources (RESs) the amount of CO_2 exhausted per kilometre approaches zero. While the benefits for the environment are apparent, the adverse effects on power systems seem less obvious to modern-day PEV owners. This section deals with the effects PEV charging has on power system management

Charging technology

Availability of charging infrastructure and the required charging time are important barriers for the widespread adoption of PEVs. PEV charging technology is often divided into three categories: slow, normal and fast chargers [11, 202].

- Slow chargers can be found in residential homes as regular power sockets. They are one-phased and offer charging times between 11 and 36 hours, depending on the battery state.
- Normal chargers are specialised charging stations, public or private, that form the primary charging infrastructure. These chargers can be either one- or three-phased and offer recharging times between 1 and 6 hours
- Fast chargers are often commercialised installations, that offer charging as a service, with quick refuelling. Fast chargers are three-phased charging docks that can lower the charging time to under an hour [11].

Within these three categories, charging infrastructure can be classified further based on the direction of flow. Unidirectional chargers only offer grid-to-vehicle (G2V), thus charging, while bidirectional chargers also offer vehicle-to-grid (V2G), i.e. discharging.

PEV load patterns

According to [170] the charging behaviour of Dutch PEV drivers is not influenced by the charge of the vehicle's battery. Rather, PEV drivers stick to routine and base their charging schedule on convenience. Between home, work and public charging, drivers most often charge at home [170]. The arrival time of PEVs at home is concentrated in the end of the afternoon, causing the PEV-specific load peak around 21:00 [85]. This charging peak time coincides to a large extent with the already occurring residential load peak [79]. Seeing the load of PEVs imposes a significant increase to a normal house load [162] the uncontrolled charging of a large PEV fleet can lead to for instance frequency fluctuations and grid failure for (de)central power systems [2, 11, 39, 64, 150, 168, 185]. [192] showed that the national peak load could increase by as much as 7% at a PEV penetration rate of 30% while more than doubling household peak load. The impact of uncontrolled charging on power grids cannot be ignored if persistent quality of the Dutch electricity supply is to be guaranteed [36, 203]. [199] shows, through field tests, that for most of the plugged-in time, PEVs do not charge. As a result, cars could be available to provide ancillary services if V2G technology is available, see 2.2.2.

Summarising, adverse effects from PEV charging are mainly caused by the uncontrolled nature of most load profiles. Although the total demand is relatively low the adverse effects are extremely dependent on charging modes [156]. [61] states that compared to normal household loads, PEV loads offer a higher amount of flexibility and elasticity. Thus, PEV could be beneficial to power grids if their charging patterns match the needs of the system, charging at otherwise low demand and possibly discharging at periods of high demand (see 2.2.2) [2, 105, 155, 164, 172]. Coordination of charging leads to power quality levels that are comparable to those when no PEVs are considered [36]. However, the current energy system design is centrally focussed, and central coordination of PEV charging is only possible under full transparency, with computationally heavy control algorithms [107]. Full disclosure of all data concerning travel patters is very unlikely to receive support from the public. Moreover, using PEVs simply to fill the overnight load valley can still lead to overloading, but simply shifted.

Peak load management
Numerous methods have been described in literature that aim at peak shifting, i.e. moving the PEV peak load away from the residential peak load. According to [24] there are three ways to optimise the exploitation of the positive effects of PEVs for the power grid (1) using pricing mechanisms (2) introducing demand response algorithms (3) and deploying and using vehicle-to-grid (V2G) technology (see 2.2.2). Most of the previous work is a combination of these three categories. For instance, a lot of the pricing mechanisms are used to achieve demand responsive charging, i.e. high prices will lead to low load.

Pricing mechanisms are used to incentivise loading at low network load and vice versa. [61] models users' readiness to change loading profiles by introducing a willingness to pay (WtP) parameter. The willingness to pay adheres to the flexibility that PEV owners have considering their travel plans and state of charge (SOC). In the model user agents adapt their WtP according to their preferences, resulting in a certain charging speed - higher WtPs result in higher charging speeds. In [39] a charging algorithm is constructed based on the usage constraints of the users. The algorithm builds on [38] and features an aggregated optimisation of the energy price over the day. Through simulation the algorithm is proven to achieve valley-filling, shifting the PEV demand peak from the evening to during the night. [107] developed a charging algorithm that includes the battery degradation cost. They show that a system-optimal strategy can be found if PEV users make a trade-off between their own charging costs and local generation costs. In [187] a method is introduced where aggregators decide on revenue-optimising energy prices. PEVs then decide on their charging profile based on their specific charging requirements. The proposed algorithm does not incorporate load problems, but does show that social optimum can be achieved through the use of PEV aggregators. According to [150] pricing algorithms can account for the intermittent character of some RESs, causing prices to rise in time of shortfall and thus low PEV load. In their research, [198] show that dual tariff pricing mechanisms, e.g. night time discounts, might cause behavioural adaptation, but is likely to damage the grid further. They conclude that communication between vehicles and grid is required so that smarter charging schemes can be introduced.

Demand responsive charging or smart charging is an aggregated control scheme to limit excessive load by PEVs at times of high network load. Usually these algorithms act autonomously without requiring human intervention, thus ruling out the need for incentives. Based on quadratic programming [79] propose an algorithm that can minimise power losses and voltage fluctuations while decreasing peak power. They acknowledge the associated costs with coordinated charging. [175] state that smart charging solely targeting valley-filling causes PEV owners to align their charging during the night, resulting in additional peak loads. [116] use load predictions to calculate desirable charging speeds and durations. Their goals are to minimise overall peak load and to balance the load profile. They show that the algorithm leads to desirable effects, while only requiring household electricity consumption data.

2.2.2. Storage capacity and vehicle-to-grid
According to [34] storage capacity can effectively lower the operational cost of distributed power systems. There are many forms of storage capacity, but especially battery technology seems very promising, as a result of recent technological advances. These advances will accelerate the adoption of distributed generation (DG) from renewable energy sources (RESs), possibly leading to an increase in the value of renewable energy [46]. As the value of renewable energy goes up and owners have reasonable certainty that value is persistent, DG is incentivised. PEVs are considered to be one of the primary sources for storage [73, 102]. [175] show that PEVs are unused for most of the day. The power invested in the automotive fleet is enormous [83], thus even when only a small proportion of parked vehicles can be connected to the grid, they can increase the quality of power supply, lower system costs and provide mitigation for the intermittence of renewable energy generation (REGs) [84, 99].

Besides having the ability to store large amounts of electricity, PEV fleets have the potential to feed stored energy back to the grid at a later, more opportune moment. This is known as the vehicle-to-grid (V2G) concept. V2G essentially is a bidirectional link between the power grid and electric vehicles, allowing them to feed power to the grid from their batteries. Already in [81] electric vehicles with V2G technology were expected to become important shapers of future energy systems. Three factors determine the maximum power drawable from any one PEV (1) the capacity of the link to the power grid, (2) the available charge over time, and (3) the maximum power of the vehicle's electric system [82]. [80] show that, due to their small storage capacity, plug-in hybrid electric vehicles (PHEVs) are less suitable to provide services through V2G. When implementing (large-scale) V2G into a power system, a trade-off has to be made between the storage requirements for the owners' driving patterns and the storage capacity required to stabilise the system by the grid operator. [83] recognise three ways to do this. (1) increase storage capacity beyond requirements of the owners, (2) aggregate until a more or less constant demand pattern is reached over a large number of PEVs, and (3) use smart control to determine when and when not to draw from PEVs. This work is focussed on the latter.

V2G can be beneficial to a number of power markets, which are discussed subsequently.

The baseload market

V2G is not competitive for baseload power [80, 82, 84]. Baseload power is relatively constant over a large period of time. Because of this, large, central, slow-ramping generation sites are used to meet this demand. As long as they can operate at full capacity, their production cost per unit of power are by far the lowest of all production facilities. Examples of production sites are coal-fired or nuclear power plants.

Peak load market

Peak (load) in power grids occurs at those times of the day the demand for electricity is the highest. Examples of this are the evening peaks, when residential areas are densely occupied, or the afternoon peaks during summer, when air-conditioning requires large amounts of power primarily in commercial sectors. On the other side of the spectrum, supply has its peak at different times. For instance, the supply peak from PV panels is around noon. Moreover, PEV drivers often plug in their vehicles during prevailing peaks, increasing the harmful effects and the difficulty to balance the system. With limited smart control the charging and discharging (V2G) of PEVs can actually benefit the grid by matching the generation with load time [80, 81]. The storage capacity of a fleet of electric vehicles can effectively bridge the gap between the two. Furthermore, a PV output curve almost entirely, albeit with a delay, matches the load curve of air-conditioners. By using PEV as temporary storage this delay can be efficiently mitigated [81]. This process is called peak shaving or shifting.

Ancillary services market

For ancillary services, such as spinning reserves and regulation, power generation sites make contracts with the TSO, saying that they will have a certain amount of available power ready for emergencies such as grid failures or sudden load peaks. Often these contracts have a minimum power of 1 MW [83]. Seeing most V2G infrastructure has a power output of around 20 kW [11, 202], either an aggregation of a large number of vehicles is required to make bids of suitable size, or a smarter system is required to lower, possibly rule out, the need for the minimum power threshold. It is assumed that the threshold is a result of the associated transaction costs. If transaction costs could be limited, aggregation could become lower, possibly to the vehicle level, resulting if a better geographical match between supply and demand of ancillary services. A design of a transactional framework that could facilitate this is presented in Chapter 5.

Through their modularity and short response time, the storage capacity of PEVs is of high value to grid operators for high-speed ancillary services. This is especially the case for the distribution grid operators (DGOs), who face increasingly dynamic local power systems. [99] show that the economical benefits for PEV owners are small if price signals from the day-ahead market will be used. However, the potential gains from encouraging ancillary services on a 15 minute basis are much greater [85, 110]. At 10% penetration rate in Denmark there would already be enough capacity to cover the required ancillary services. [46] recognise that with present-day technology, PEV batteries could already provide commercially effective solutions for instantaneous, short term and medium term ancillary service. Especially on the medium term, a fleet of PEVs could be used for load balancing and peak load shaving. Allowing PEVs to function as a spinning reserve for power grids could be an economic incentive for owners. Namely, generators get paid a rate for every hour they are available to the grid plus an extra, market-conform price for any sold unit of electricity [82, 182]. Compared to spinning reserve, regulation requires shorter load duration, quicker response times (less than a minute) and is required more often [82]. [182] states that regulating is the best market for V2G to operate on, due to its high market value, low impact on the battery lifespan and especially battery electric vehicles are well outfitted to perform regulating due to their ability to exert continuously fluctuating output [50]. [133] states that the ancillary market could be filled by only a small number of vehicles.

Intermittence of REG

For the two most important RESs, wind and sun, coping with intermittence is an important aspect for power quality. Of the two, wind energy is the most variable, while sun energy is relatively constant and more predictable. However, the time of peak supply doesn't match that of peak load. To account for the intermittence of REG, two modes of operation are possible: backup and storage. Backup is used to account for failures at generation level. Using their ICEs to provide power to the grid, or PEVs with fuel cells (H_2) [83], PEVs can deliver power when a part of the grid is in islanding mode. Storage is expected to be the only economically viable option, namely it can be provided by any PEV possessing a battery and in combination with V2G offers direct economic incentives. For PV and wind energy, storage can account for their unpredictability and displacement between peak power and load. [105] says that by using V2G a much higher share of energy from RESs can be achieved, compared to DG systems without a V2G fleet, as the technology can effectively help match time of generation and time of load. They use EnergyPlan [53] to model an hour-to-hour representation of Denmark's power grid. Their input parameters featured a high penetration of combined heat and power (CHP) and wind energy. [110, 163] also recognise the importance of V2G for the value of REG.

V2G costs

[81] show that the expected benefits from using the storage capacity from PEVs will outweigh the potential costs. Due to parking costs the PEV fleet is actually generating negative value [186]. Moreover, because constant fluctuations and failures in the grid account for 5-10% of electricity costs [82], DGOs could subsidise PEV owners if they help mitigate these harmful effects.

V2G systems require intensive software investment, but little effort in developing or adapting hardware [81]. [105] adopted a model that makes sure every individual car is fully charged before it is disconnected, but refer to [81] for the possibility of using pricing mechanisms in order to incentivise charging during low demand/high supply and vice versa. Economic benefits can be achieved by replacing regular generation with discharging of PEVs, seeing their low capital cost, similar availability and the possibility of matching supply and demand at much shorter distances [81, 82, 182]. This economic competitiveness is regardless of the high per unit production costs [83]. The owner of the car needs to be encouraged to plug in the PEV whenever the car is parked [68]

Battery degradation

One of the most important cost drivers for V2G technology and a critical hurdle to overcome is the stress on PEV batteries. Battery degradation is defined as the loss of a battery's charge capacity [71], and is caused by quick fluctuations in charge and deep discharging. Considering most modern-day PEVs have lithium-ion batteries [9, 18, 37, 111, 190] and discharging can have devastating effects on the lifespan of such batteries [46], a trade-off must be made between cost and benefits. Intermittent charging may also shorten the battery lifespan [107], [103] goes as far as claiming that V2G is not a viable option yet because of the degradation that occurs. According to [71] charging should be stopped around 85-90% state of charge (SOC) to avoid severe degradation. The effect of high SOC on degradation is also mentioned by [106, 196].

Controversely, [132] states that the effect of V2G on battery degradation is less than half of that of rapid charging/discharging during driving. Furthermore, they state that the depth of discharge (DoD) is an unsuitable indicator for battery degradation in these situations, and instead suggest using the total amount of processed energy. High level of intermittence in charging/discharging should be avoided. [204] show that lithium-ion batteries can be cost-effective if used for peak load V2G, but economics are highly dependent on ambient temperatures and DoD. In a pilot experiment [17] showed that, when used for regulation, the battery requirements for V2G were similar to that of regular driving and that the benefits exceed the incurred costs. The economic feasibility of V2G regulation is further substantiated by [74]. They state that around 50% state-of-charge (SOC) battery degradation is lowest at different ambient temperatures.

2.2.3. Penetration rate in the Netherlands

According to [145] there were almost 13 000 BEVs and 86 200 PHEVs on the Dutch roads by the end of 2016. When compared to the total number of passenger cars, approximately 8.1 million, the penetration rate of

PEVs is roughly 1%. Tables 2.1 and 2.2 show the distribution of some of the most popular PHEVs, respectively the most popular full electric vehicles (BEVs) in The Netherlands. For the PHEVs only the top five most popular models are used due to the large diversity of available PHEV models, the remaining 'other' fraction's battery capacity is calculated as a weighted average of these five models. Some car models might come in multiple different versions, including different battery capacities. If that is the case, a medium-sized battery capacity is selected as to not under- nor over-estimate the available capacity.

Table 2.1: Table of the most common PHEVs in The Netherlands with market share [145], and battery type and capacity [57, 88, 118, 120, 181].

Model	Percentage	Battery type	Battery capacity [kWh]
Mitsubishi Outlander	28.8%	Li-ion	12
Volvo V60	17.4%	Li-ion	12
Volkswagen Golf	11.3%	Li-ion	8.7
Audi A3 Sportback	6.1%	Li-ion	8.8
Mercedes Benz C350 E	5.9%	Li-ion	6.2
Other	30.5%		10.7

Table 2.2: Table of the most common full electric vehicles in The Netherlands with market share [145], and battery type and capacity [37, 67, 69, 124, 142, 165, 173, 179, 180, 188].

Model	Percentage	Battery type	Battery capacity [kWh]
Tesla Model S	46.5%	Li-ion	75
Nissan Leaf	13.7%	Li-ion	30
Renault ZOE	10.9%	Li-ion	22
BWM I3	6.7%	Li-ion	33
Renault Kangoo Z.E.	5.4%	Li-ion	22
Nissan E-NV200	5.3%	Li-ion	24
Smart ForTwo	3.8%	Li-ion	17.6
Renault Twizy	3.6%	Li-ion	6.1
Tesla Model X	2.1%	Li-ion	100
Volkswagen Golf	2.0%	Li-ion	24.2

According to [101] 61% of Dutch public charging stations have been 'smartified'. It is assumed that the process of smartification results in charging infrastructure that can offer V2G capabilities to a car.

2.3. Problem definition and implications for design

Concluding from the previous sections a number of weaknesses can be spotted in the current organisation of the Dutch power system:

- Resulting from Dutch and European policy, the energy market was liberalised. Consequently, the system conveyed optimal conditions for the rise of decentralised generation. With the increasing penetration of REGs, such as wind and energy, prosumers, companies and (local) governments give ear to the rising concern for the environment. While the system is clearly decentralising, the control strategy is still marked by a top-down, centralised approach. This is evident from the responsibilities of the TSO as the central party responsible for grid-wide balance.

- Thus, decentralised generation has a increasing share of REG. RESs, especially wind and sun, are highly intermittent, which makes the supply hard to predict. As a result, additional stress is imposed on the central balancing responsibility and REG investment conditions are sub-optimal.

- Road traffic is one the most important sources of CO_2 emissions. Therefore, the wide-spread adoption of electric vehicles can have significant benefits for the environment. However, as the current system has no smart way of controlling charging patterns, the introduction of PEVs leads to additional stress on decentralised power systems. This is especially relevant for the household peak load, which is to a large extent coincident with the preferred charging time of PEVs. These peaks are therefore intensified.

- Stability in decentralised power grids is increased by the availability of local storage. Collectively, the batteries of PEVs could provide ample capacity to provide useful services to grid system operators, not in the last place due to their large idle share. Nonetheless, owing to the central nature of control strategies, this potential is wasted. To reach service thresholds aggregation is required, of which the proposed algorithms are complex and cumbersome.

In short, PEVs' stabilising potential is wasted and the energy transition is progressing slower than it could due to the system's top-down approach. If the benefits of the energy transition are to be exploited fully, the power system requires a new, bottom-up design. The first step in solving balancing problems at the consumer level should be amongst consumers themselves, peer-to-peer (P2P). This would be in line with the prosumer movement, where users of the electricity systems take up an increasing interest in participation. However, the current system design has no way of facilitating the active participation of the smallest user level. In order to reach capacity thresholds, designed to optimise economies of scale and minimise transaction costs, small consumer would have to be aggregated. As consumers are aggregated the resulting control strategies move further away from individual user preferences. On the other hand, should P2P energy trading be implemented, active involvement would require knowledge of energy markets and basic economics. User adaptability is therefore also an issue.

2.3.1. Design criteria

The remainder of this work will focus on the applicability of PEVs to facilitate electrical grid stability and the design of a transactional system that can meet the decentralisation of Dutch power systems. In the (near) future, the design can be expanded to gradually overtake critical system responsibilities, for example those currently belonging to the TSO. The system will have to allow for PEV owners to offer their services directly to peers, cutting out USPs and BRPs, allowing a form of direct market participation. In order to achieve this, transaction costs should approach zero and the system has to be able to provide instant response and account for a large transaction throughput. P2P transactions occur between individuals that have no way to knowing, and thus trusting, each other. Third parties, such as banks, could be introduced to act as trusted party. However, this would mean handing over sensitive information over to new actors. In an age of decreasing privacy and rising concern for it, this might result in a less attractive solution. Moreover, the man-in-the-middle approach would incur additional transaction costs and move away from decentralised principles.

Without a trusted third party, system security becomes an important obstacle to overcome. In the P2P network it is likely that two parties have no established trust relationship and thus require some other mechanism to check the authenticity of users. Moreover, in a distributed network, no one node has indisputable authority to validate the system state. Thus, the system requires a way of validating transaction integrity in a distributed sense. A technology that could facilitate this is blockchain.

Blockchain is the technology behind the more well-known Bitcoin. The technology was dubbed as a timestamping server [121], but later came known as blockchain. Blockchain is essentially a distributed ledger that allows users to exchange assets without interposition of for instance banks. Instead, these parties are replaced by mechanisms of cryptography and rely on maths and IT instead of central actors to keep the system running. Blockchain is extensively addressed in Chapter 3.

2.3.2. Research questions

The main research question is:

How can electric vehicles promote energy transition and how can blockchain facilitate the decentralisation of such energy systems?

EVs will become an integral part of our society as we move away from fossil fuels and prepare for a more sustainable future. The main objective of this research is to investigate how EVs can be of use for future energy systems, rather than put additional stress on them. The extent to which blockchain can help in this is also considered, the following sub-questions convey this notion:

- What is blockchain and how can it facilitate decentralised utilities?
- What are likely user adoption scenarios for blockchain-based energy trading?

- How will different user attitudes affect system performance?

3 Blockchain

A blockchain is a fully distributed ledger, containing transactions. More specifically, all transactions relating to the specific blockchain ever made. The technology was first introduced in 2008 by Satoshi Nakamoto as the technology underpinning the ever-popular Bitcoin [121]. Bitcoin is a cryptocurrency where trust is no longer put in central minting authorities, but in the underlying cryptography mechanisms of a blockchain. Thus, blockchain-based systems would meet the need for transparency and equality of liberalised energy markets. However, by removing a central trusted authority, security becomes the next key issue. Moreover, in a blockchain where value comes from energy there is essentially no minting process, namely energy is generated. Furthermore, requiring a lot of energy (as is inherent to Bitcoin as explained in 3.3) to be able to trade energy seems ironical. In other words, if the blockchain as proposed by [121] would be used to facilitate energy markets a number of questions needs to be answered:

1. What is a suitable model of consensus for a transactional system for energy markets?
2. What is the required frequency of consensus, i.e. block creation, for such a system?
3. Would the system benefit from a private, public or hybrid blockchain?
4. What roles can current market parties play in such a system?

This section contains an overview of blockchain's concepts in 3.1 and the different modes in 3.2. Following, in 3.3, four different consensus models are explained.

3.1. Blockchain concepts

In order to fully understand the applicability of blockchain for energy markets, some of the core concepts, as well as essential underlying crypto mechanisms, are discussed here. Most of these notions are taken from [121].

Transactions are the core of any blockchain. The main reason for introducing blockchains, was so that conventional three-party trust relations could be replaced by a two-party transactional system. Trust in a third party, such as a bank, is replaced by trust in mathematics, more precisely: cryptography. Each transaction contains a sender $Alice$, a transaction message m and a receiver Bob. transactions are performed in such a way that after each valid transaction, ownership is transferred rather than copied.

Digital signatures are what chains the transactions together. Digital signatures are used to verify integrity of a transaction message and authenticity of the transaction sender. One method of digital signaturing is using RSA. RSA is, amongst others, used as an asymmetric (public key) cipher system, meaning that messages are encrypted and decrypted using different keys, as opposed to symmetric cipher systems where the same key is used for encrypting and decrypting [166]. RSA is based on the difficulty of factorising large integers. Say $Alice$ wants to sign a transaction to Bob, he/she she picks two secret large primes p and q:

$$N_A = p_A * q_A \,, \tag{3.1}$$

and an encryption exponent ε_A, such that

$$gcd(\varepsilon_A, \phi(N_A)) = 1\,, \tag{3.2}$$

where gcd stands for greatest common divisor and $\phi(N_A)$ is Euler's totient function of N_A. Because p and q are primes $\phi(N_A) = (p-1)(q-1)$. (N_A, ε_A) is considered the as public part and (d_A, p_A, q_A) the secret, where

$$d_A = 1/\varepsilon_A \mod \phi(N_A)\,. \tag{3.3}$$

As $Alice$ sends m and the signature

$$s_A = m^{d_A} \mod N\,, \tag{3.4}$$

Bob can check the authenticity of $Alice$ and the integrity of m by verifying that

$$m = s_A^{\varepsilon_A} \mod N\,. \tag{3.5}$$

The transaction message m is formed by a previous transaction, where $Alice$ was the receiver, and Bob's public key. This provides a link between the current transaction and the previous ones, verifying ownership of the transacted item by $Alice$. Using string m as input for RSA can take a long time (as a result of exponentiating), especially if m's length increases. Therefore, hashes are used instead.

Hash functions are used to save time when signing transactions. A hash function takes an input string of arbitrary length and outputs a string with a fixed length. They are said to be one-way, meaning that it is easy to compute a hash from a given string, but computationally infeasible to compute the string belonging to a given hash [166]. Good hash functions adhere to a set of rules, resulting in no correlation between input and output. This means that even if only one input bit is changed, the output could be completely different. By using hash functions $Alice$'s signature becomes

$$s_A = h(m)^{d_A} \mod N\,, \tag{3.6}$$

where $h(m)$ results in a hash of m, i.e. $h(x)$ is the hash function (e.g. SHA-256 for Bitcoin [92] and Keccak-512 for Ethereum [201]). The verification is now done by sending m and s_A to Bob, who can verify using $Alice$'s public key to find

$$h(m) = s_A^{\varepsilon_A} \mod N\,, \tag{3.7}$$

by comparing with the hash from the received message (m') a signature can be verified by checking if

$$h(m') = h(m) \tag{3.8}$$

For instance, if $Alice$ were to send some item with value x to Bob, she would have to prove that she has received x in an earlier transaction, for example from $Charles$. The message that $Alice$ sends to Bob would be

$$m := txn_{n-1}(Charles \longrightarrow Alice, x, \varepsilon_B)\,. \tag{3.9}$$

The digital signaturing scheme is graphically represented in Figure 3.1.

Although the receiving end of a transaction can now verify authenticity and integrity of the transaction message, i.e. verify ownership, there is no way for him/her to check if the sender had not already spent the transacted item. This is also called the **double spend problem**. In order words, there is still no actual transference of ownership. This problem is solved by timestamping, namely creating blocks.

Blocks are aggregations of transactions that are timestamped together. By including the hash of the previous block, blocks are linked together into the blockchain. Because blocks are linked together using hashes, changing the block's content would completely change all subsequent blocks. Consequently, every block is immutable after enough consecutive blocks have been added. Blocks, and thus all included transactions, are unique because timestamps are added. The process of creating blocks is called mining. In this process, miners compete for reaching widespread consensus.

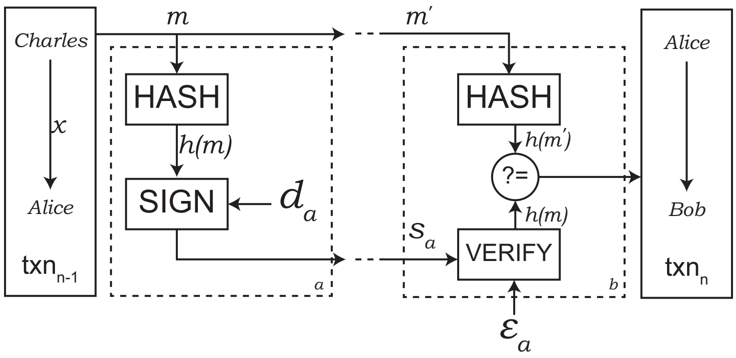


Figure 3.1: A graphical representation of the digital signaturing scheme used in blockchain transactions

Consensus or majority voting, is the process of deciding on one single correct blockchain in a distributed network. Usually, a consensus algorithm depends either on encouraging honest nodes or punishing dishonest ones. For instance, Bitcoin's consensus model is called proof-of-work. It requires miners to invest in energy and in return they receive a reward for succesfully mining a block. The longest chain is considered to be the correct one, seeing it has the most invested into it. Simultaneously mined blocks lead to forks. For this reason transactions are only fully confirmed after a number of blocks have been added after the containing block - with Bitcoin this is 6 blocks, i.e. roughly an hour. After this confirmation time has passed, forks are either merged with the main chain, or dropped. Different consensus models are described in Section 3.3. Because of the distributed nature of blockchains, 51% attacks are introduced.

51% attacks are a result of the distributed trust algorithms in blockchain applications. Because of the way consensus works on blockchains, integrity is dependent on the share of honest nodes. If more than half of the nodes is dishonest, i.e. a node (collection) possesses more than 50% of the network's resources, the blockchain's consensus algorithm can no longer guarantee that the longest chain is indeed the correct/honest one.

Merkle trees are introduced to save disk space. Merkle roots are, often binary, hash trees where the lowest level is formed by hashes of the data and the top level is called the root hash. According to [92] whenever a non-miner node needs to verify a transaction he only needs to have the transaction hash and the root hash. For instance, if a node wants to check TXN_1's occurence in the respective block in figure 3.2 he/she only has to receive $HASH_2$, $HASH_{34}$ and $HASH_{5678}$ from a mining node, who keep a record of a larger part of the chain. By concatenating hashes the verifying node can work up to the top of the tree and check the resulting root with the one given in the block header. The difficulty of verifying a transactions is said to be $log(N)$.

3.2. The four Ps of blockchain

The original blockchain was a fully public one, 100% decentrally controlled. However, this structure is not applicable for all possible timestamped ledger applications. Different applications require different levels of security. In an effort to characterise (existing) blockchains, a two-dimensional classification system was introduced. The two axes are formed by data access and mining priviledge. Data access runs from private to public and mining privilege from permissioned to permissionless [13, 14].

Private vs. public blockchains

Public blockchains, such as Bitcoin, grant full access to the data stored in the blockchain, as well as authorising all nodes to add new transactions into the pending pool. It is needless to say that private blockchains prohibit such access. Blockchain was based on the trustless principle, meaning that transactions can occur between two parties that have no reason to trust each other, apart from the underlying algorithmic paradigm. For the same reason Satoshi [121] made Bitcoin open-source, as the collective testing power of all nodes, by far supersedes the testing capability of any private organisation at much lower costs [159]. Moreover, public blockchains protect the users from the developers as anyone is free to verify the correctness of the inner

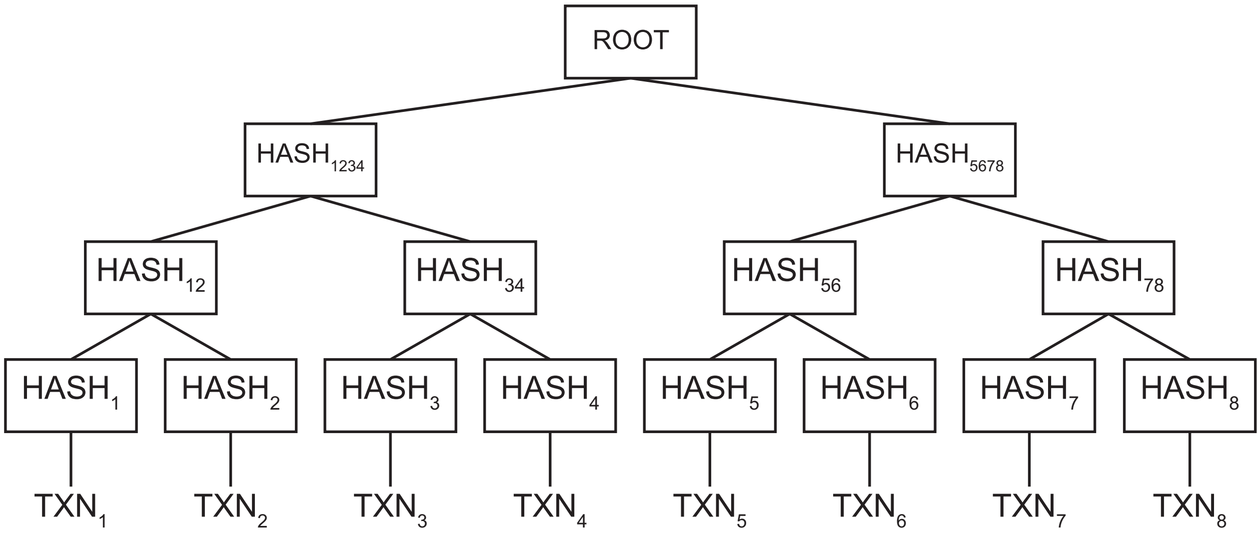


Figure 3.2: A graphical representation of a Merkle tree

workings of the blockchain [20]. As a blockchain become more private, more and more benefits of blockchain technology are undermined [13]. However, private blockchains are not completely useless, they find their domain within companies as facilitator of various business flows [119].

Regulated blockchains, or consortiums, form a trade-off between private and public blockchains. Instead of having a black-and-white perspective, specific access is granted to some or all users. Rights can be given to either read, write or both, and joining can be open to anyone or some users, based on registration criteria [13, 20].

Permissioned vs. permissionless blockchains
Permissionless and permissioned blockchains are distinctive in how consensus models work. On permissionless blockchains anyone can partake in the mining process, whereas permissioned blockchains limit the amount and kind of nodes that can vote on block creation. On permissioned chains the identities of miners are known, or either traceable, thus the required consensus models can be lighter versions than that of permissionless systems. This results in lower transaction costs and higher block speeds [20]. Moreover, permissionless mining leads to un-evenly split network power, as is the case with Bitcoin's PoW, where access to external resources determines mining success [14]. As [200] states, 51% attacks were already possible in 2014 due to large mining pools, where combined resources could outmatch the rest of the network. Due to the fact that immutability is theoretically never guaranteed, transactions confirmation takes a very long time (with Bitcoin it is one hour), just to be reasonably safe [14].

3.3. Consensus models in blockchain

There are a number of consesus models available that aim to achieve agreement in distributed sytems. This section covers four of them: (1) proof-of-work (PoW); (2) proof-of-stake (PoS); (3) Byzantine Fault Tolerance (BFT); (4) Federated Byzantine Agreement (FBA).

Proof-of-work
PoW can be considered as the traditional consensus model described by [121] in 2008. Whenever a miner tries to mine a block, containing any number of transactions, he creates a block header. Block headers H contain the previous block's header, the Merkle root hash ρ and an integer nonce i, see figure 3.3.

$$h(H_n) = h(H_{n-1} \parallel \rho_n \parallel i)\,. \tag{3.10}$$

The mining process entails hashing the newly created block header (equation 3.10) and incrementing the nonce until a hash is found that meets a certain difficulty. The difficulty relates to a number of starting zero bits n. For instance, in Bitcoin, SHA-256 outputs strings of 256 bits. If we look at the integer result of $h(H_n)$ is should hold that

$$h(H_n) < 2^{256-n} . \tag{3.11}$$

The difficulty is set to a moving average number of blocks per time unit based on the technological state-of-the-art in the network (changed roughly every two weeks [92]). Once a block is mined it can be added to the chain and the network starts on mining the follow-up block. The miners are incentivised to mine through setting the first transaction of a block, called coinbase in the Bitcoin blockchain, as a reward for the miner. At the time of writing the reward is approximately 12 BTC, or almost €6,900. Besides being incentive, the coinbase is also the main minting process of PoW consensus models.

Mining thus entails reproducing the same useless hash calculation, requiring miners to invest in significant CPU/GPU power if they want to earn the coinbase. Thus, PoW is a great way of ensuring value of a cryptocurrency, however it comes with two important downsides: (1) the PoW consesus protocol results in an extremely high energy consumption due to the high dependence on CPU/GPU power [42, 109] and (2) the Tragedy of the Commons problem

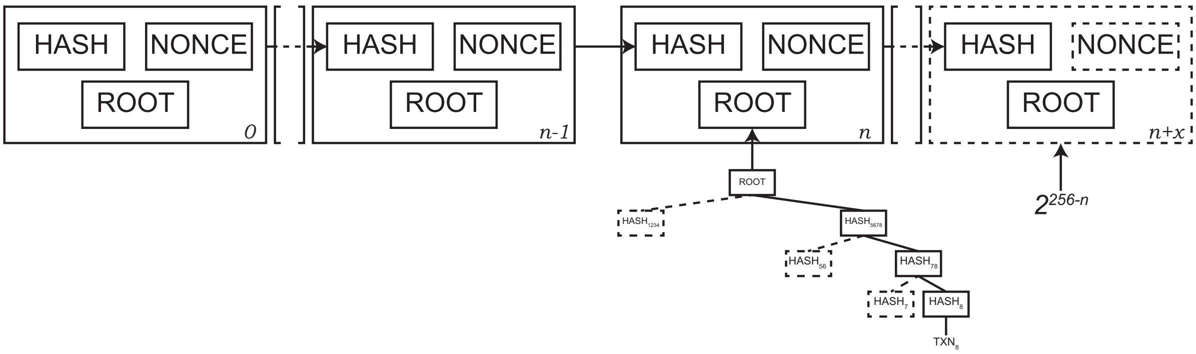


Figure 3.3: A graphical representation of consequtive block headers in a proof-of-work consensus algorithm

Tragedy of the Commons is described in economics as a system of shared resources where individuals act based solely on their own self-interest, collectively moving away from a common optimum [75]. The TotC is often explained by using grazing herds of cattle. Herders who let their cattle graze on common grounds benefit from buying extra livestock as to increase their share over their competitors. However, supply (fresh grass) is limited by nature, eventually resulting in a depleted field. This is analogous to e.g. Bitcoin mining where the supply of the initial reward is decreased over time and the demand (CPU/GPU power of miners) is increased in hopes of getting a higher succesful mining rate. Eventually, the rewards will no longer cover the costs of running expensive mining equipment, demotivating nodes to stay honest. On the long-term, PoW will not be able to guarantee healthy cryptocurrencies.

Proof-of-stake

Proof-of-stake (PoS) was introduced by [87] as a model of consensus for Peercoin, an alternative cryptocurrency and is essentially a verification of ownership. PoS works with two type of blocks, PoS and PoW blocks. PoS blocks are known in the database and memory, but not to the network [41], i.e. the blockchain is formed entirely of PoW blocks. In PoS models the miners use a stake $\mathcal{S}$, an unspent wallet output with a certain age $t_{\mathcal{S}}$, lower bound to t_{min}, to make a kernel $\mathcal{K}$, which contains [41, 86, 125]:

1. a random 8-byte modifier to introduce randomness (used to prevent pre-staking), R;
2. the timestamp of the block containing the stake coin transaction, $t_{H_{\mathcal{S}}}$;
3. the offset of the stake coin transaction inside the respective block, O;
4. the timestamp of the stake coin transaction, $t_{\mathcal{S}}$;
5. the output/amount of the stake coin transaction $N_{\mathcal{S}}$;
6. the current timestamp t_{now} (see figure 3.4).

All kernel inputs are concatenated and hashed to form

$$h_{\mathcal{K}} = h(R \parallel t_{H_{\mathcal{S}}} \parallel O \parallel t_{\mathcal{S}} \parallel N_{\mathcal{S}} \parallel t_{now}) \,. \tag{3.12}$$

Similar to PoW $h_{\mathcal{K}}$ is matched to a certain difficulty, which is inversely proportional to the staked output [19, 86], so the hash requirement becomes

$$h_{\mathcal{K}} < \tau * N_{\mathcal{S}} * (t_{now} - t_{\mathcal{S}}) \,, \tag{3.13}$$

where τ is a target per unit coin age and $N_{\mathcal{S}} * (t_{now} - t_{\mathcal{S}})$ is the staked coin-age. If the difficulty of the kernel is not met, the current timestamp is reset to match the UTC time in seconds and re-hashed. If the difficulty is met, the stake output is spend in a coinstake transaction, similar to Bitcoin's coinbase, in the newly timestamped PoW block. The block award and any transaction costs are added to the coinstake and act as incentive for miners [129].

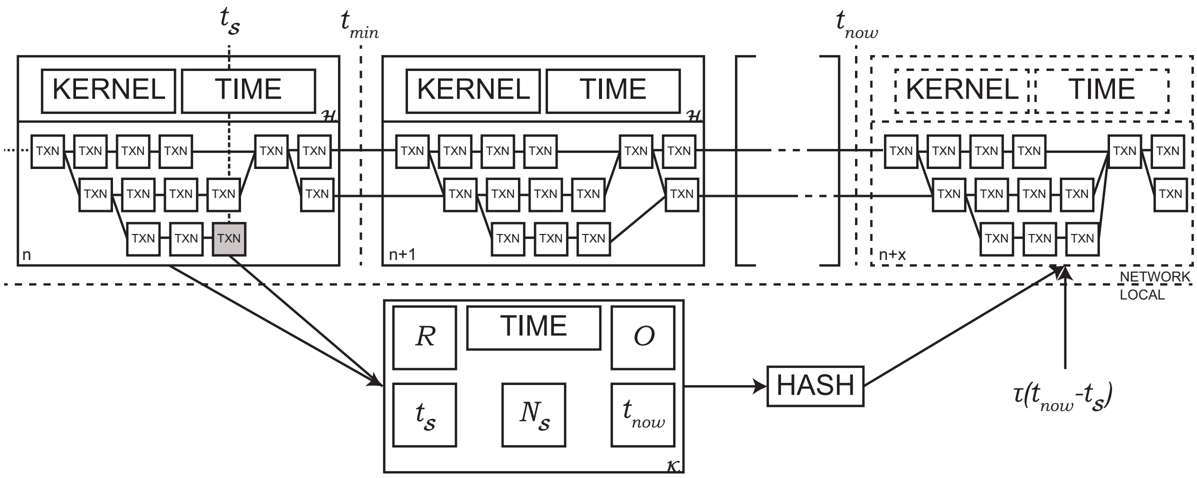


Figure 3.4: A graphical representation of how the kernel in a proof-of-stake algorithm is formed and used in a proof-of-stake blockchain

Because difficulty is inversely related to unspent wallet outputs, 51% attacks are only possible if a node attains more than 50% of the coins in the network. Moreover, because the hashing rate is limited to 1 per second per unspent wallet output, only a limited number of hashes can be generated, resulting in a much more energy efficient system. However, the PoS consensus algorithm does introduce the "nothing-at-stake problem".

Nothing at stake is caused by the fact that there is no actual cost of mining. In traditional PoW systems miners have invested in computational power, which is most efficiently used on one chain. In the event of forks, miners gain nothing from splitting their CPU/GPU power, as it would lead to decreased success rate on both chains. For PoS systems ther is no additional cost for mining on multiple forks at once, therefore the mining success rate increases by mining on all available chains: a miner will get a reward regardless of on which chain a block is mined [22]. Solutions to the nothing-at-stake problem have been suggested, such as the Slasher algorithm [21], but have not seen (large-scale) implementation.

Byzantine Fault Tolerance

The Byzantine Generals Problem (BGP) was first introduced by [98] as an abstraction for problems in embedded computer systems. The analogy of generals in the Byzantine army that need to agree on a common battle plan through a single communication channel, can be used to describe e.g. blockchain systems. The nodes in the network are analogous to the generals, a traitorous general being a dishonest node and a loyal general an honest node. The to be agreed upon common battle plan is the valid blockchain, where disruptions caused by traitorous generals are symbols for forks of the main chain (be it malicious or not). By solving the problem a resolution is found for conflicting information in distributed networks, i.e. a consensus model. According to [98] the network nodes must all be aware of the same information and have an uniform, robust algorithm to process the information, as described by [25]. A Byzantine Fault is then arbitrary, deviant behaviour of nodes. In essence Byzantine fault tolerance (BFT) is a voting system that requires a 2/3 majority vote to achieve consensus.

A blockchain using a solution to the BGP as a basis for the consensus model is Tendermint [94]. In their Byzantine Consensus Algorithm (BCA) block creation is achieved by validators, known nodes that have staked coins and a corresponding amount of voting power. Nodes in the validator pool are selected to become proposer in a round-robin fashion, in proportion to their voting power. Each round the proposer multicasts a proposal for a new block $\mathcal{B}_n$, composed of a header $\mathcal{H}_n$, transaction data set $\mathcal{T}_n$ and the previous block's validation set $\mathcal{V}_{n-1}$:

$$\mathcal{H}_n = \{ID, n, t, h(\mathcal{H}_{n-1}), h(\mathcal{T}_{n-1}), h(\mathcal{S}_n)\}\,, \tag{3.14}$$

where the ID is the blockchain's string id, n is the proposed block height, t is the local time of the proposer, $h(\mathcal{H}_{n-1})$ is the hash of the previous block's header, $h(\mathcal{T}_{n-1})$ a root hash of the previous block's transaction Merkle tree and $h(\mathcal{S}_n)$ a root hash of the state Merkle tree after adding the proposed block [95].

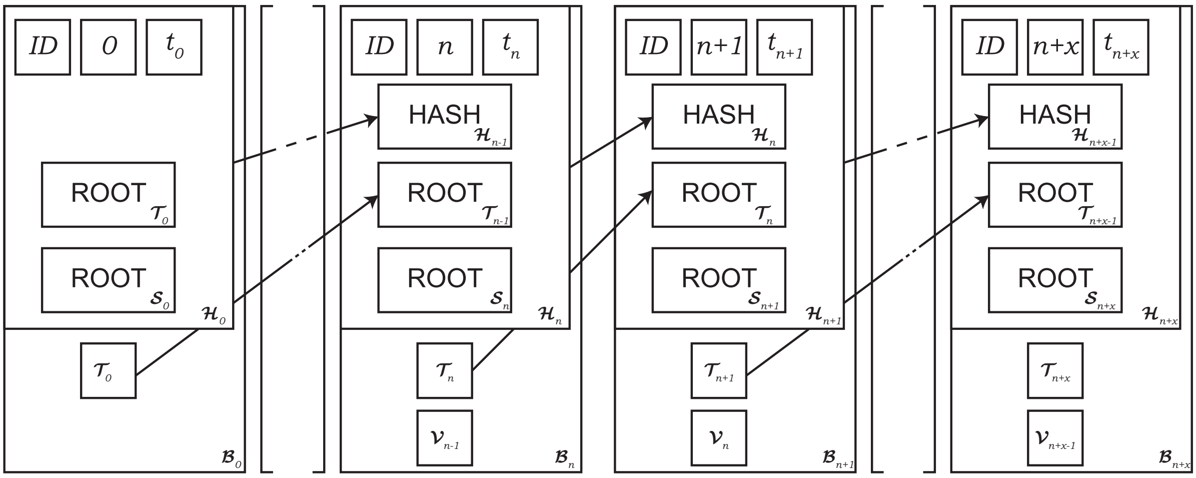


Figure 3.5: A graphical representation of how blocks are linked in a Byzantine fault tolerant blockchain

After a block is proposed the validators enter the prevote step, during which each validator multicasts a prevote vote to neighbouring nodes. A vote $\mathcal{V}_i$ from node i contains the

1. the integer block height, n;
2. the round number, v (after [25]'s view);
3. the type (prevote or precommit), $\in \{1,2\}$;
4. the hash of the proposed block's header, $h(\mathcal{H}_n)$;
5. the blockparts (used to speed up multicast) $\mathcal{B}_n$;
6. the validator's signature, s_i [95].

Essential during voting is the locking state of a validator. A validator i can be locked on a block proposal from any previous round (offset x). Each node can be locked on zero or one block(s) and can only vote for the locked proposal block. If the validator does not receive a valid block proposal during prevote it votes nil. Locking happens during the step following prevote, namely precommit. During precommit every validator locks a block if it has received more than 2/3 of prevotes for that particular block, while simultaneously multicasting a precommit vote to its neighbours. Seeing every validator can only lock on one block at a time, it unlocks on any other block. If a node receives more than 2/3 prevotes for nil it simply unlocks and a new round is started. If 2/3 of the validators precommits are found for a specific block, the block is committed, timestamped, hashed and added to the chain. Subsequently, a new voting round is started for a new proposal [55, 94, 96, 161]. Each round, proposal, prevote and precommit, is bound to pre-defined timeout times, increasing marginally every round, allowing for (partially) asynchronous networks.

Algorithm 1: Tendermint's Byzantine consensus algorithm

```
Data: v = 0
begin
    begin proposal step
        v := v + 1;
        pick proposer;
        proposer proposes block (n, v);
        if proposer is locked on block from previous round v_lastlock then
            add proof-of-lock (PoL) from v_PoL;
    begin prevote step
        foreach validator i do
            if proposal is invalid then
                i ⟶ {nil, s_i};
            else
                if i is locked on block from previous round then
                    if ∃PoL && v_lastlock < v_PoL < v then
                        unlock;
                    if i is still locked then
                        i ⟶ {n, v + x, 1, h(H_n), B_n, s_i};
                else
                    i ⟶ {n, v, 1, h(H_n), B_n, s_i};
    begin precommit step
        foreach validator i do
            if i receives more than 2/3 nil prevotes then
                unlock;
                v_PoL := v;
                GoTo proposal;
            else if more than 2/3 prevotes for the same block with a height n then
                i ⟶ {n, v, 2, h(H_n), B_n, s_i};
                v_lastlock := v;
                v_PoL := v;
    if more than 2/3 precommits for particular block then
        t_commit := t_now;
        add block n to chain;
        restart algorithm;
    else
        GoTo prevote;
```

Safety in consensus is based on the fact that validators can only vote once per block height, and double votes can easily be spotted by other validators. In case of duplicate votes the bonded coins of the infringing node are destroyed. Thus, dishonesty is directly, economically discouraged.

Federated Byzantine Agreement

A comparable algorithm to Byzantine fault tolerance is federated Byzantine agreement (FBA). An example of a FBA is the Ripple Protocol Consensus Algorithm (RPCA). In RPCA there is a set of validator nodes, or servers, I, in which every server i maintains a proposal set of transactions to be verified and added to a block:

$$\forall i \in I \exists \mathcal{T}_i^v \,, \tag{3.15}$$

$$\mathcal{T}_i^v := \{T_1, T_2, ..., T_k\} \,, \tag{3.16}$$

where v is the round number and $v = 0$ is used for a candidate set. Servers are registered in unique node list (UNL), denoted $\mathcal{U}$. During a set of iterative rounds v, the servers compare their candidate sets and/or proposals. If a transaction occurs in both proposals, the server votes for that transaction and if the number of votes is more than a specified voting rate τ, the transaction is added to the proposal for the next round.

$$\sum_{k=1}^{\mathcal{T}_i^v} \left[\sum_{j \neq i}^{\mathcal{U}} \left(\frac{f\left(T_k, \mathcal{T}_j^v\right)}{|\mathcal{U}|} \geq \tau \right) \implies T_k \in \mathcal{T}_i^{v+1} \right] , \tag{3.17}$$

where

$$f(T_k, \mathcal{T}_j^v) = \begin{cases} 1 & T_k \in \mathcal{T}_j^v \\ 0 & otherwise. \end{cases} \,. \tag{3.18}$$

The voting rate is increased every round from 50%, to 60% and finally 70%. Network consensus is reached when more than 80% of $T_k \in \mathcal{T}_{i,3}$ has a 70% occurrence or higher. The block, including all those transactions, is added to the blockchain. The transactions that have not received a voting rate of 70% or higher remain in the candidate set and a new voting process is started. The speed of the network, which is in the order of seconds per block, is dependent on the latency between nodes. If nodes exhibit a latency above a certain threshold, they are dropped from all UNLs, in order to speed up the network [149, 160].

The Stellar framework, which started out as a hard fork of Ripple, but later started a new code-base, is to a large extent the same as Ripple, which different nomenclature. A validator pool, or UNL, resembles Stellar's quorum and a quorum slice can be seen as a candidate set or proposal. Slots are basically block numbers/heights and an update is used to describe a new block being added to the chain. The only difference that Stellar introduces is the notion of open membership, opposing Ripple's default UNL, and UNL alteration rules [112].

Algorithm 2: Ripple Protocol Consensus Algorithm

```
Data: v = 0, τ = 0.5
begin
    while v < 3 do
        foreach transaction k ∈ T_i^v do
            n_k = 0;
            foreach server j ≠ i ∈ 𝒰 do
                if k ∈ T_j^v then
                    n_k := n_k + 1;
            if n_k / |𝒰| ≥ τ then
                k ∈ 𝒯_i^{v+1};
        v := v + 1;
        τ := τ + 0.1;
    if |𝒯_i^3| / 𝒯_i^2| ≥ 0.8 then
        consensus reached;
        𝒯_i^3 broadcasted as new block;
        faulty transactions are removed;
        remaining transactions are added to new candidate set;
        restart algorithm;
```

4

Scenarios of the energy transition

The current Dutch electricity system was to a large extent designed from a pre-renewable energy perspective. The top-down approach, where a few large power plants supply the needs of many consumers, can not account for the increasingly decentralised imbalances occurring as a result of the energy transition. The energy transition is characterised by an increase in the number of electric vehicles and a growing penetration of renewable energy. These trends will set the requirements for a local trading architecture. Therefore, Future scenarios owing to the energy transition are the focal point of this chapter.

This chapter gives a description of the different scenarios that used as input for the model described in Chapter 5. Subsequently, Sections 4.1 trough 4.3 present the scenario variables for electric vehicles, renewable energy generation and finally public charging. The effects of decentralised trading on grid operational effectiveness will be reviewed following a set of criteria presented in section 4.4.

4.1. Electric vehicle penetration

The amount of PEVs in the model will be varied to analyse the effects of the electrification of the automotive fleet. The results will give insights in what the possible bounds are for using PEVs as grid support.

According to [26] 71.5% of Dutch households owns at least one passenger car. 48.4% owns one car, 18.8% owns two cars and the remaining 4.2% owns three or more (three cars is assumed in the model). The modelled neighbourhood would own a cumulative 75 cars. In order to investigate the effects of PEVs on distributed power systems, a number of household agents will be given an electric vehicle. The other cars are irrelevant for the analysis and hence left out of the model. The number will be based on actual purchase dates of passenger cars published by RDW, the Dutch governmental agency responsible for the road network. By the beginning of 2017 there were 13,105 full electric vehicles (BEVs) and 98,903 hybrid electric vehicles (PHEVs) with a registered Dutch license plate. Compared to the total of 8,100,864 passenger cars [31] the penetration of PEVs is approximately 1% [143, 144] (see also figure 4.1). The base scenario will feature a BEV fraction of 1%. The distribution for the specific car type and model and corresponding battery capacity is presented in section 2.2.3. It is assumed that users have a home connection for charging their PEV, with a stochastically assigned power outlet. According to [202] type 1 and 2 chargers are used at home. However, no probability distribution is known of home chargers, thus power outputs with 1.4 kW, 1.9 kW, 4 kW, 8 kW and 19.2 kW will be drawn from a uniform probability distribution.

Scenario 1 will feature a short-term future scenario, in 2025. According to [171] there will be an 85% increase of PEVs in respect to 2017. The assumption is backed by the fact that Tesla's Model 3 is due to be released in 2018. It offers a saloon car with an action radius of over 300 km at an affordable price of 35000 USD [178]. The car is in popular demand and is expected to reach 20,000 sales by 2018 alone. In accordance an 85% increase seems an underestimation. According to [77] the adoption of BEV will be much more rigorous, namely 25% of all passenger cars by 2025. They base their claim on decreasing financial incentives for ICE cars and PHEVs, while agreeable conditions will occur for driving fully electrical. The BEV fraction is assumed to increase to 80%.

Scenario 2 relates directly to plans of the Dutch cabinet and businesses to phase out cars with internal com-

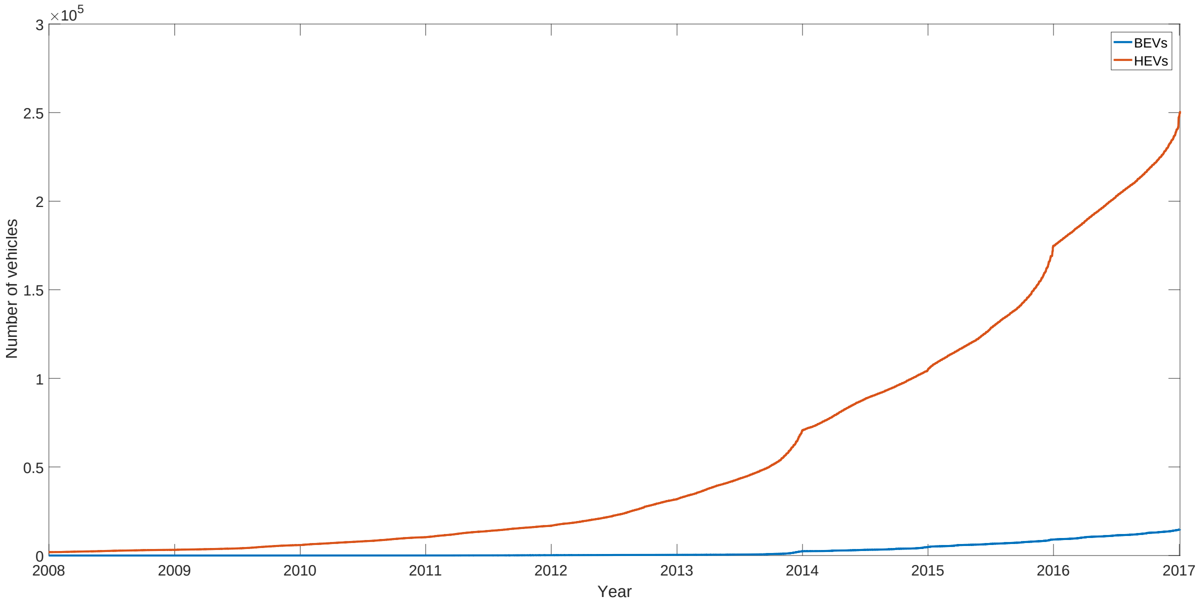


Figure 4.1: Number of electric vehicles in The Netherlands from 2008 to 2017 [143, 144]

bustion engine (ICE) and gradually replace them by EVs. As agreed upon in the Energieakkoord (energy agreement) in 2013, by 2035 every newly sold car should be able to operate in CO_2-neutral mode [167]. This includes both BEVs and PHEVs. The Dutch state wants to achieve a much more radical change, and prohibit the sale of cars with ICEs completely by 2025 [194]. Seeing the contradiction with earlier policy, it is unlikely that the resolution will be effectuated. However, it is probable that in the long term The Netherlands will face a large share of PEVs. Moreover, as battery technology advances and larger action radii come at lower prices, it is assumed that the share of BEVs will increase further. In agreement with experts at CGI, a penetration rate of 80% PEVs, with a 90% BEV share, by 2035 is assumed.

The arrival and departure of PEVs at households is stochastically assigned using (truncated) normal distributions. Their parameter values are presented in Table 4.1. They are based on an eight-hour working day, from 9:00 to 17:00 and resembling the resulting distribution plots to everyday expectations.

Table 4.1: Arrival and departure times of PEV normal distribution parameters

Lower bound	Upper bound	Mean	Standard deviation
0	24	8	0.4
0	24	18	0.4

4.2. Penetration of renewable energy generation

Electric vehicles will support the decentralised grid by offering a balancing factor. Balancing is required because of deviations between forecasted and actual demand. One major instigator of these deviations is the presence of REG. BRPs deal on the market based on the aggregation of a large number of household electricity profiles and yearly estimated consumptions (YECs). However, due to their inability to predict for instance solar radiation, and thus PV output, BRPs might under/overestimate consumption and are forced to buy balancing services at a very high rate. In order to examine how REG affects decentralised grid operation and what the boundaries are for effective use of local storage from PEVs, the penetration rate of REG will be varied across several simulation experiments. According to [117] the estimated share of homes with PV panels in The Netherlands is 6%. The data in the CEMS database covers only homes that have PV panels, thus only 6% of it will be used in the base model.

Scenario 1 will face a penetration of REG of 20%. According to [148] the Dutch government expects 14% of all energy to be generated from RESs by 2020 and 16% by 2023, compared to their estimated current penetration of 5%. The current percentage of households with PV panels closely resembles that, thus the amount of PV panels is assumed to grow proportionally to 17% by 2025.

Scenario 2 is in accordance with the Dutch government's plans to have an all-renewable energy portfolio by 2050 [148]. Seeing the absence of more data points, the growth of REG is assumed to be linear, which would result in a REG penetration of approximately 57% in 2035.

4.3. Public charging behaviour

[45] used a large dataset (over one million samples) of Dutch EV public charging sessions to distinguish three kinds of public charging behaviour:

1. *Charge near home* features people that charge their cars during the night at a charging station near home. Of the over 90,000 sessions in the analysed subset, 29.1% belonged to this cluster. The cluster was identified by connecting in the afternoon or evening and disconnecting during the subsequent morning.
2. *Charge near work* is the cluster of EV owners that park their car near their workplace or during their commute to work. 9.4% of the sessions recorded could be accounted to this type of charging behaviour. The users credited to this cluster connect during the morning and disconnect during the evening of the same day.
3. *Park to charge* users exhibit sojourns that closely approximate the net charging time, most likely meaning that the sole reason for parking was charging. The connect/disconnect times are randomly scattered over the day. 61.5% of public charging sessions were identified as such.

Figure 4.2 shows the probability distribution for charging amounts of public charging stations in The Netherlands. Rather than modelling travelling patterns and corresponding charging behaviour, a pre-defined amount of energy is stochastically assigned each time an EV is plugged in, publicly or at home. This simulates the user's preference for minimum state-of-charge for future trips. The number of public charging stations is estimated to be 5, based on geographical information on charging stations in The Netherlands [126]. The number of public charging stations is assumed to grow relative to the penetration of BEVs. Thus scenario 1 will feature 15 public stations and scenario 2 will have 50. Public station's use will be modelled stochastically, based on sojourn and idle times presented in [45]. Only the sub-clusters considering departure within 24 hours are considered. According to [58] the average occupancy of station public charging stations is 13.4%, which will be used to stochastically determine the occupancy of modelled stations.

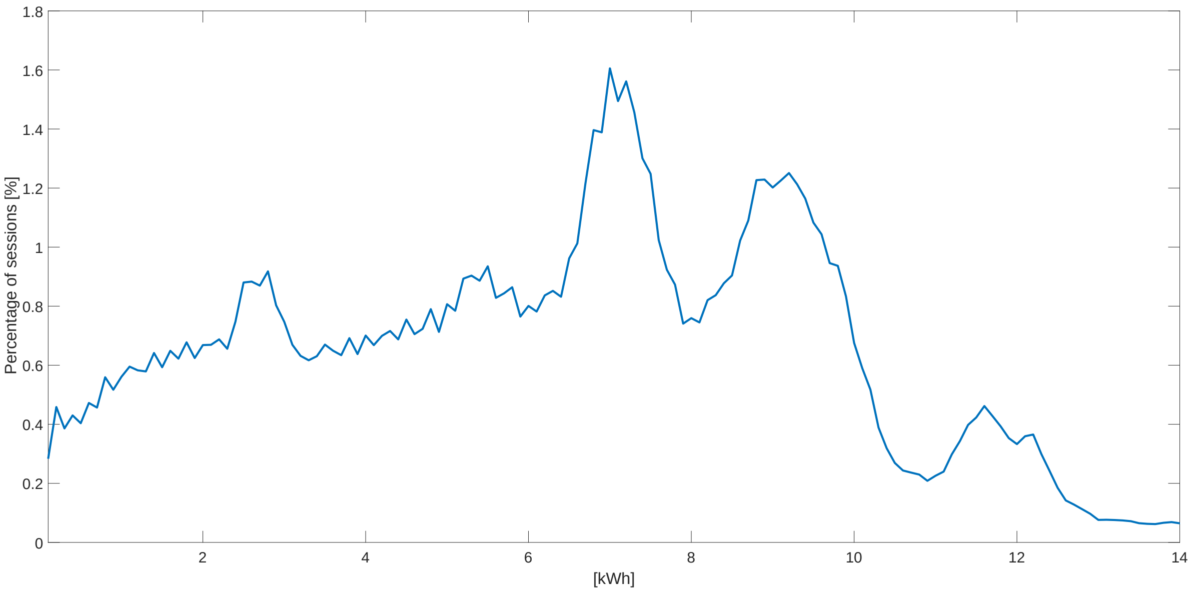


Figure 4.2: Probability distribution of charging amounts in The Netherlands [60]

4.4. Criteria

There is a clear distinction between performance on a system level and on the individual user level. From a system's perspective the main purpose of local trading is to balance estimated and actual demand, thus avoiding the need for expensive intraday market trading. Therefore, the main criterion for assessing the effective stabilising effect of PHEVs on decentralised power grids is the difference between estimated and total actual demand, i.e. household and PEV load. Any decentralised supply can be seen as negative demand and therefore has a negative impact on this criterion if not used locally.

Another important system criteria are the performance requirements for blockchain. Blockchain technology faces a trade-off between scalability and performance. Because a permissioned blockchain is a likely choice for this implementation, scalability, i.e. the number of nodes partaking in the consensus algorithm, is of lesser importance compared to performance. Performance deals with the number of transactions that can be processed/validated per time unit, in other words: the transactional throughput. Therefore, the number of transactions performed in the model will be used as a second criterion from the system's perspective. Agent logic will be used as a simulation for smart contracts. The number of transactions that pass the agent logic will be used to calculate throughput under different grid circumstances.

The proposed system in this research project requires input from its users. Thus, an important barrier for the technology's success is the willingness of users to adopt the system and adapt their energy consumption routines. [44] found that households were capable of shifting 15% of energy consumption to meet local solar supply. [93] conducted an analogous analysis based on smart appliances and a local supply of solar energy. Based on a forecasted amount of sun radiance and a user-defined ultimatum finish time, consumers can profit from cheap, local and clean energy for their semi-autonomous washing machine. The three categories for consumer motivation: environmental issues, financial incentives and interest in innovative technology, are also key indicators of the technology designed in this work. Moreover, according to [89], [93]'s research was used as input for designing the 'Jouw Energie Moment' (JEM), or Your Energy Moment, pilot project. One of the conclusions drawn from the project, was that around 70% of the participants were actively seeking the optimal electricity consumption time based on price [113]. From the database it is evident that 78.4% of JEM participants chose an electricity plan based on price, meaning their smart appliances would schedule based on price signals from the APX. The remaining participants chose an eco plan, meaning their appliances would spring into actions if their PV panels would output electricity. Based on these considerations, costs associated with charging will be used as a means to test performance from a user's perspective.

It is likely that during times of underestimation the system would benefit from discharging PEVs, which introduces the risk of (near-)empty batteries. If this would be the case at PEV departure from its charging station, users might become reluctant to partake in local trading. Therefore, the performance from a user's perspective will also be measured using the SOC at PEV departure.

5

Design and testing of a decentralised architecture for local electricity trade

In our current system generation is matched to load from the top down, based on predictions rather than actuality. As a logical effect, mismatches arise between what is expected to be consumed and actual load, forcing market parties to even out using expensive intra-day trading. Due to imbalance being caused at the end of the value chain, at the highest market participant density, errors proliferate upwards in the chain, causing substantial market inefficiencies. Additional errors are caused by an increasing share of distributed energy generation and uncontrollable plug-and-charge behaviour of electric vehicles. By shifting the control structure from central to decentralised, from top-down to bottom-up, the upward propagation of balance uncertainty can be stopped. To facilitate this paradigm shift, trading between decentralised production and load must be enabled, for which the current system offers no handholds. Facilitating local trade might be the missing catalyst for the energy transition.

Therefore, this chapter is dedicated to presenting a design of a system that could facilitate the aforementioned paradigm shift through facilitating peer-to-peer energy trade in smart grids. A model was developed to, on the one hand, analyse the effects of electric vehicle charging on distributed grids. While, on the other hand, implementing business logic as if it were smart contract logic, following the principles of blockchain 2.0. Under the assumptions of local trade, various grid conditions are tested on their balancing capacity, transactional requirements and user implications. In Section 5.1 a description of the input data, as well as the modelling and simulation environment is provided. In the next section, 5.2, the results of the simulation study are presented, including the scenario analyses and important output predictors that were found during model validation (see Appendix B). Finally, the results are used to present a implementation of the architecture on a blockchain in Section 5.3. A detailed specification of the model can be found in Appendix A.

5.1. Experimental setup

An agent-based model (ABM) was developed to analyse the effects of PEV charging behaviour when introduced in a smart microgrid environment. In their book on artificial societies, [56] described the modelling of complex phenomena derived from the interaction of a large number of individual entities. Modelling agents that can interact with the environment following a set of elementary rules, can help in understanding emergent behaviour in various social contexts [15]. By using agent technology, simple car battery models, grid conditions and social trends can be used to examine the applicability of a PEV fleet as grid support. Conclusions from the modelling study can result in valuable insights concerning strategies for the implementation of blockchain-based energy trading in a broader sense.

5.1.1. Input data

The base of the model is formed by a Dutch neighbourhood. The model will feature 107 agents simulating households. The number is based on the number of participants, and thus individual data cases, in the input data. The input database was taken from the central energy management system (CEMS), a tool developed by CGI Nederland B.V. to balance decentralised grids. The database contained data of the first CEMS pilot project. Over a period of three years quarter-hourly smart metering data was collected of household energy consumption. The simulation span will cover a week, from 5-9-2016 through 11-9-2016. This choice was based on the limitations resulting from the internal memory requirements for attaching large databases to the modelling software. The database's historic consumption patterns will be compared to the expected consumption patterns based on electricity load profiles [122] of 2016. Electricity profiles define, for each 15-minute interval, a fraction of the yearly estimated consumption (YEC). According to [54] YEC is calculated based on metering data of the 12 months leading up to a period, thus the YEC is calculated by summing up consumption over 2015 for each individual household. The profile category *E1B* was used because the participating households had different tariffs for day and night consumption. The input project had a running time from the 6th of September 2011 until the 31st of August 2014.

CEMS data from the JEM project was collected into two databases: `CEMS` and `CEMS-Research`. Due to the absence of documentation concerning the primary database, a database model was constructed using the research database (see figure 5.1). The data was then read from the primary database in a separate model database using C# and hosted on a local instance of a Microsoft SQL (MSSQL) server.

A specific agent is identified using the `Id` field of the `Houses` table, which is assigned during the initialisation phase of the model. It is referred to in other tables as the `HouseDimension_Id` field. Together, `Dates.Id` and `Periods.Id` define unique periods of 15 minutes over the simulation period. These fields are referred to as `DateDimension_Id`, respectively `PeriodDimension _Id` in other tables. Based on these three keys the data can be read from the database. Figure 5.1 shows a graphical representation of the relevant database parts, table 5.1 gives an explanation for the data fields that were used. The database was expanded with a table containing the electricity profiles, i.e. fractions of YEC per 15 minute interval, of 2012, 2013 and 2014, called `ElectricityProfiles`.

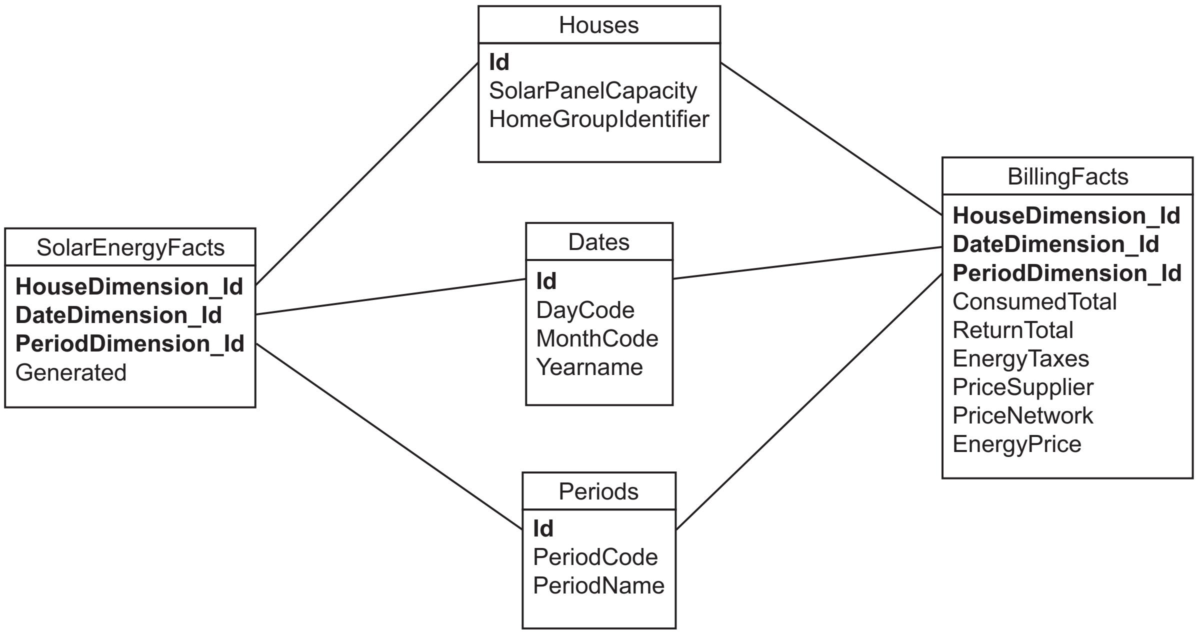


Figure 5.1: Database diagram of the relevant part of the CEMS database, containing the JEM data

5.1.2. Agents

AnyLogic [5] was chosen as software tool, as it offers a direct connection with MSSQL server instances. The model contained four types of agents as sub-agents of the model's Main agent. What follows is a brief explanation of the four agents and their relationships. For a thorough description of agent logic, please refer to Appendix A.

Household agents form the backbone of the smart grid model. Households are generated based on the input data stored in the CEMS database, thus owning an Id and YEC. Based on the Id energy patterns are loaded from the database for every 15 minute interval, i.e. period, of the simulation time. The YEC was used to calculate estimated consumption patterns, that were stored with the amount of consumed and generated elec-

Table 5.1: Explanation of CEMS data fields [33]

Table	Fields	Data type	Description
Houses	Id	int	Unique key identifier for the houses in the CEMS database
Houses	SolarPanelCapacity	decimal	Capacity of a household's PV installation in kilowatt peak (kWp)
Houses	HomeGroupIdentifier	string	The database cover multiple projects, the one, used in this work is "ZWL'
Dates	Id	int	Unique key identifier for the dates in the CEMS database
Dates	DayCode	int	Numerical representation of the day of the month
Dates	MonthCode	int	Number of the month, ranging from 1 to 12
Dates	YearName	int	Year
Periods	Id	int	Unique key identifier for the periods in the CEMS database
Periods	PeriodCode	int	Code belonging to a period
Periods	PeriodName	string	String representation of a day's 15 minute intervals
BillingFacts	HouseDimension_Id	int	Keyed link to the `Houses` table
BillingFacts	DateDimension_Id	int	Keyed link to the `Dates` table
BillingFacts	PeriodDimension_Id	int	Keyed link to the `Periods` table
BillingFacts	ConsumedTotal	decimal	Total electricity consumption in Wh
BillingFacts	ReturnTotal	decimal	Total electricity fed-back in Wh
BillingFacts	EnergyTaxes	decimal	Taxes paid over consumed electricity
BillingFacts	PriceSupplier	decimal	Average price over two hours paid to the utility supplier
BillingFacts	PriceNetwork	decimal	Average price over two hours paid to the DSO
BillingFacts	EnergyPrice	decimal	Total price for the consumed electricity, summation of previous three price fields
SolarEnergyFacts	HouseDimension_Id	int	Keyed link to the `Houses` table
SolarEnergyFacts	DateDimension_Id	int	Keyed link to the `Dates` table
SolarEnergyFacts	PeriodDimension_Id	int	Keyed link to the `Periods` table
SolarEnergyFacts	Generated	int	Production from PV panels in Wh

tricity data in watt-hours. In the base situation 107 agents are modelled, but this number can be decreased by removing households from the back of the list, or increased by duplicating database entries. Household agents can own a PEV agent, stochastically assigned by drawing from a Bernoulli experiment, using the PEV owners fraction as success rate. Another Bernoulli experiment, based on the REG owners fraction, is used to model the appropriate REG penetration. If a household does not have REG, its patterns of generated electricity are not included in the aggregated curves or trading algorithms.

Charging station agents simulate the public charging infrastructure in the grid. Charging stations have a statechart with two states: unoccupied and occupied. Each agent is created in the unoccupied state and gets a power output by drawing from a uniform distribution of 3.7, 7.4, 11 or 22 kW. Charging stations can transition from the unoccupied to the occupied state when a PEV agent arrives. PEVs arrive at charging stations following an expression based on the average occupancy. When a connected PEV's sojourn time has passed it is destroyed and the charging station agent transitions back to the unoccupied state.

PEV agents can either be owned by a household or connected to a charging station agent. Household PEVs are created at model start-up, while PEVs are created at any stochastically drawn time during simulation. PEVs have a statechart with six states:

1. The **connected** state is entered immediately after creation. In this state it is decided whether the PEV

is fully, or hybrid electric through Bernoulli draw, where the success rate equals the BEV fraction. Subsequently, a PEV model is assigned, based on the penetration in the Netherlands (see Section 2.2.3), and the corresponding battery capacity (in Wh) is set. After the connected state a PEV transitions to the scheduling state.

2. In the **scheduling** state household-owned PEVs get a stochastically assigned departure time (see Table 4.1). All PEVs get a energy demand drawn from the distribution shown in Figure 4.2, after which the battery level is decreased accordingly. After scheduling the PEV either enters the charging state immediately if smart charging is disabled or if smart charging is enabled and assigned by the aggregator, or the idle state in all other situations.

3. In the **charging** state the PEV's energy consumption is set to the amount allocated by the aggregator if smart charging (and with it local trading) is enabled, or else the maximum output per period given the charger type of the parent agent. In the charging state, the PEV's energy consumption is added to the aggregated energy curves. From the charging state a PEV can transition to the idle state if its battery is full or charging privileges are revoked by the aggregator, or to the discharging state if assigned by the aggregator.

4. Nothing happens with a PEV during its **idle** state. Idle PEVs wait out their remaining sojourn time or for the aggregator to assign (smart) charging or discharging privileges, or, in the case of household PEVs, transition to the disconnected state if their departure time has been reached. PEVs connected at public charging stations are destroyed if their sojourn time expires.

5. The **discharging** state closely resembles the charging state, except the energy consumption is negative. From the discharging state the PEV can go to the charging state if charging privileges are assigned, the idle state, or the disconnected state if its parent is a household agent.

6. In the **disconnected** state a number of variables are reset, such as sojourn time, energy demand and session charging costs. More importantly, an arrival time is assigned, which if reached, results in a transition back to the scheduling state.

At every time step (15 minute interval) PEVs check for a number of constraints. These include a battery level higher than zero, a SOC lower than 1.0, a non-zero energy consumption in the charging and discharging states and a zero energy consumption in other states. Moreover, it checks if emergency charging is required, meaning that if the time required to reach full battery charge at maximum charging power equals the remaining sojourn time, a PEV immediately transitions to the charging state.

The aggregator agent executes the trading algorithm, containing most of the business logic that would be required to run a smart contract layer on top of a blockchain protocol. It takes all households and connected PEVs into account and spreads charging or discharging allocation equally. The aggregator algorithm is given in Appendix A.

5.1.3. Model validation

The ABM was validated using a parameter variation experiment, wherein the input parameters were varied over uniform ranges and important criteria statistics were collected. Based on the resulting input-output combinations a standardised multiple regression analysis was performed. By testing one-tailed significance levels, with directed alternative hypotheses, the models output could be validated with the expected behaviour by looking at the polarity of partial regression coefficients. Moreover, by looking at the absolute size of the coefficients conclusions could be drawn on which indicators have a strong causal relation with which output parameter, leading to some of the simulation experiments described in the next section. The detailed description of the validation phase can be found in Appendix B.

5.2. Simulation results

Table 5.2 shows the parameters of the scenarios formulated in Chapter 4. They form the foundation for all experiments conducted to test the performance of local energy trading in smart grids. In the following sections (5.2.1 through 5.2.4) different grid conditions are tested on their effects on key performance indicators (KPIs), based on the criteria given in Section 4.4.

Table 5.2: Parameter values for the base, short term and long term scenario

Parameter	Base scenario	Short term	Long term
Car owners fraction	0.72	0.72	0.72
PEV owners fraction	0.01	0.25	0.80
REG owners fraction	0.06	0.17	0.57
BEV fraction	0.01	0.80	0.90
Public charging stations	5	15	50
Average occupancy	0.134	0.134	0.134
Number of households	107	107	107

5.2.1. Analysing the balancing effect of local trade

One of the prime reasons to facilitate trade between energy peers, is to mitigate the mismatches that occur between estimated consumption and actual consumption. If these imbalances can be solved de-centrally, accumulation of errors on a central scale could be minimised. Using the scenarios described in Section 5.2 the effects of local trade on estimation deviance is analysed and presented in the subsequent paragraphs.

Base scenario

Figure 5.2 shows a single run of the base scenario with 6% REG, and 1% PEV penetration. The dotted red line displays the grid's household consumption. Where the household consumption is above the solid black line, representing the estimated consumption of the grid, there is underestimation and vice versa there is overestimation. The solid green line represents the amount of electricity from REG. Whenever there is available renewable energy, the consumption drops. The household consumption together with PEV demand, both household and publicly charging vehicles, is represented by the solid red line. It is evident from Figure 5.2, where the red, solid line tops the dotted red line, that, in this specific run, PEV demand increases imbalance during periods of underestimation. If a household owns a PEV, a charging output is assigned from the uniform distribution described in Section 2.2.3.

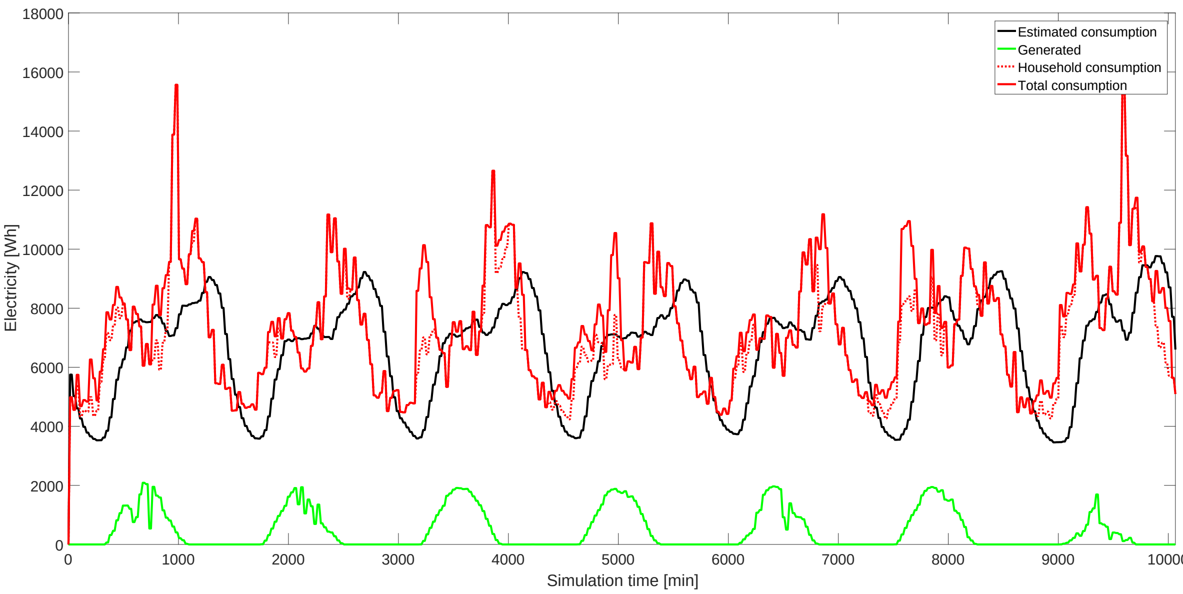


Figure 5.2: Output of a single run of the ABM model in the base scenarios (6% REG penetration, 1% PEVs)

To test the influence of stochastic variables in the model on simulation behaviour Monte Carlo experiments were conducted with 30 runs using unique random seeds. The resulting plots are shown in Figure 5.3. Over all runs, for each 15 minute interval, the minimum (solid cyan line), mean (solid red line) and maximum (solid blue line) total consumption is collected. By comparing the two plots in Figure 5.3a and 5.3b, the effect of PEV charging on grid balance can be investigated. Moreover, the use of local energy trading in a smart grid can be analysed as a balancing solution.

From the figures it can be concluded that on average, when looking at the difference between mean total consumption and household consumption, PEVs and local trade offers positive effects on grid balance during times of underestimation. This is shown by the solid red line dropping under the dotted red line. When there is no local trade, on average there are only undesirable effects (the solid red line almost always exceeds the dotted one).

This can be explained by looking at the extreme cases: the minimum and maximum total consumption. Due to the stochastic nature of arrival and departure, PEVs can cause demand peaks throughout the day. When local trading occurs the highest maximum value is slightly lower, but on average the peaks are higher. This is a result of discharging and the emergency charging fail safe: when PEVs sell energy back to the grid, they increase the full SOC charging demand. Without local trade the minimum total consumption always matches the household consumption, as in the base scenario the chance of not having a plugged-in PEV is substantial. However, with local trade the minimum total consumption (solid cyan line) better approximate the estimation (solid black line). This is especially the case for periods of underestimation, giving the first sign that V2G and local trade can help in balancing estimation and consumption.

Predictions for the short term future

Figure 5.4 shows the energy pattern plots of the short term Monte Carlo experiments. When reviewing the plots in Figure 5.4a and 5.4b it is concluded that, without trade, PEVs increase underestimation. With trade enabled the average maximum value of demand peaks is increased. Under the influence of local trade peaks seems to occur more periodically, there where the average total consumption (solid red line) spikes up together with the maximum total consumption. These peaks happen around 8:00 in the morning, right before the afternoon demand valley. The pattern shows that the mean total consumption tends towards the max, meaning over all runs large demand from PEVs occurred at these times. For the remaining time periods the mean total demand tends towards the minimum total consumption, illustrated in solid cyan. As the minimum total consumption follows the estimation (solid black line) it can be concluded that over all runs local trading tends to balance the grid.

Predictions for the long term future

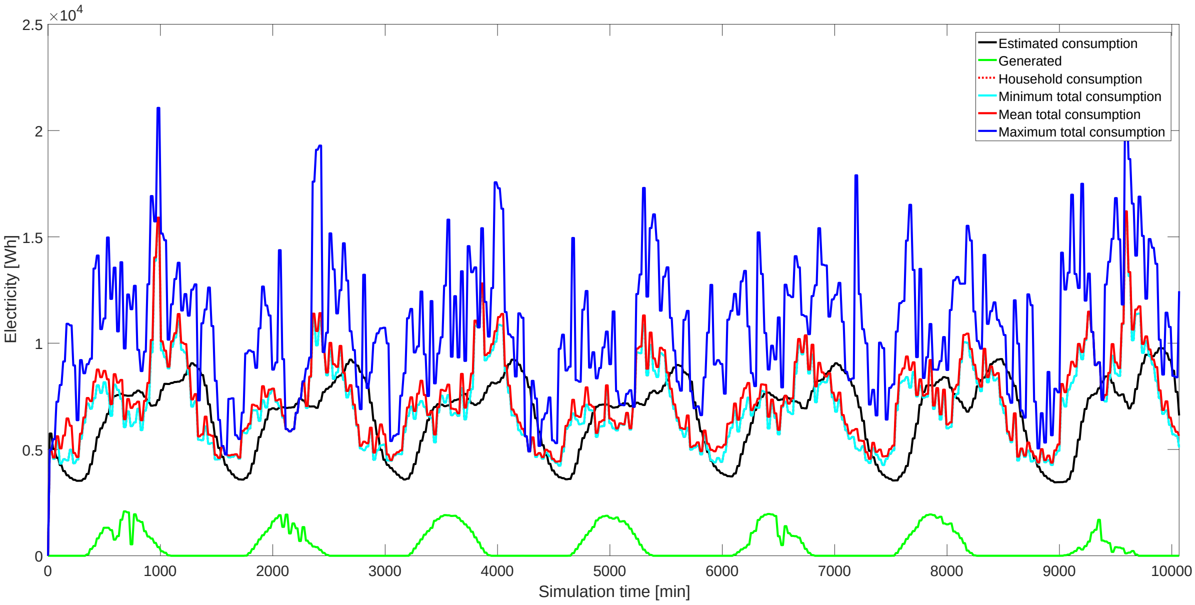
The results of the long term future scenario, presented in Figure 5.5, build on the conclusions drawn from the first two scenario experiments. PEV demand peaks around the end of the morning, while during the rest of the day local trading offers a significant reduction in the deviance between estimated and actual consumption. On the long term, the penetration of REG will increase to a level that would result in grid net production. The severity of the demand peak overshoot has increased to dramatic levels in the long term scenario, sometimes increasing grid consumption with more than a 1000%. Within the characteristics of the modelled grid, it is challenging to balance such large mismatches in the grid with local trading alone. However, these peaks appear to occur strongly periodical (see Figure 5.6b). Compared to the non-trading scenario (Figure 5.6a), less noise is present and only one demand peak per day is present.

Statistical tests for balancing effects

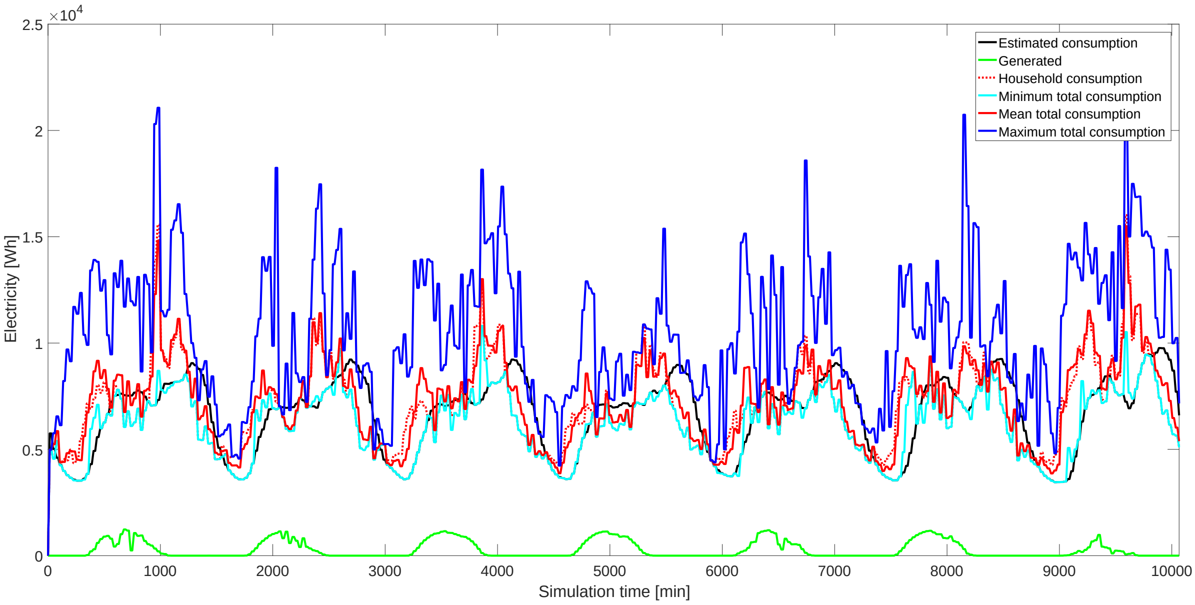
To statistically analyse the effect of local trading on the grid's deviance from estimated consumption an independent samples t-test was conducted. The test analyse the equality of means in two groups, in this case trading and no trading, of the same sample, in this case the three scenarios. The null hypothesis is that the means of the cases (N = 30), each case represents mean deviance over one simulation run, in both groups is equal. If the statistic's p-value lies under the significance value ($\alpha = 0.05$, corresponding to a 95% confidence interval) the null hypothesis can be rejected. Table 5.3 shows the results of the statistical test. It can be concluded that for all three scenarios local trading offers a significant reduction in deviance. The means are lower, standard deviation smaller and thus the 95% confidence interval is narrower. Consequently, not only does local trading decreases the deviance, it also makes it less volatile, allowing for better predictions and tighter safety margins for BRPs.

Periodicity and predictability of smart charging behaviour

The periodicity of the consumption patterns is analysed using cross-correlation and compared between trading and non-trading scenarios. Cross-correlation is a measure for resemblance between a dataset and a shifted version, with lag λ, of the dataset. As the simulation time step was 15 minutes, $\lambda = 1$ corresponds to 15 minutes. Looking at the plots in Figure 5.6, it seems that the deviance follows a daily pattern. This is

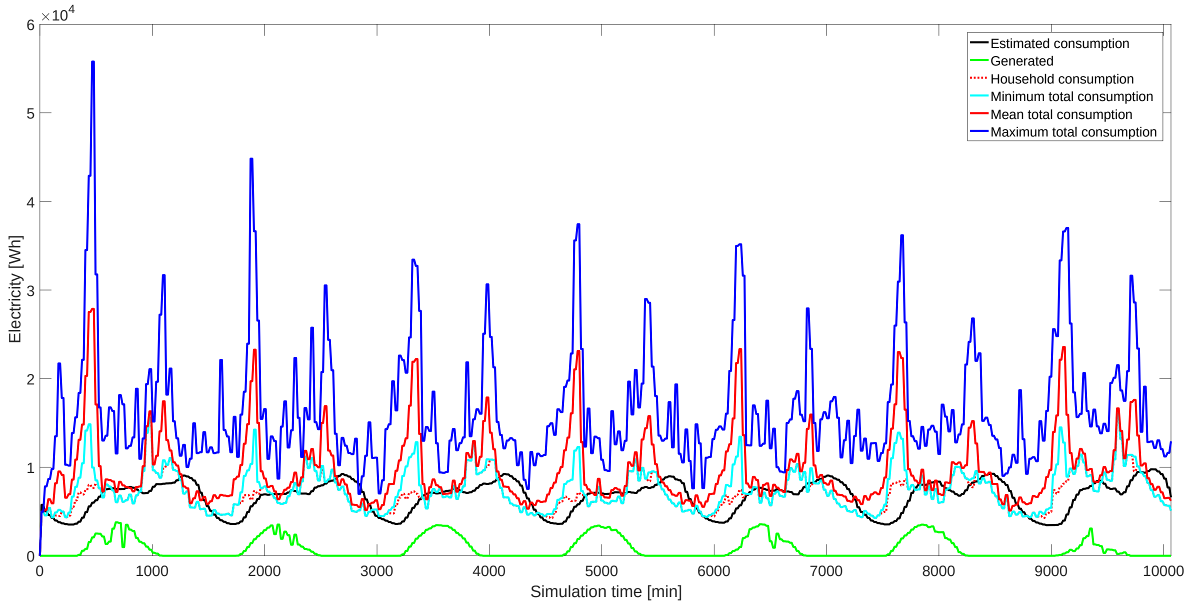


(a) Monte Carlo (N = 30) experiment of base scenario

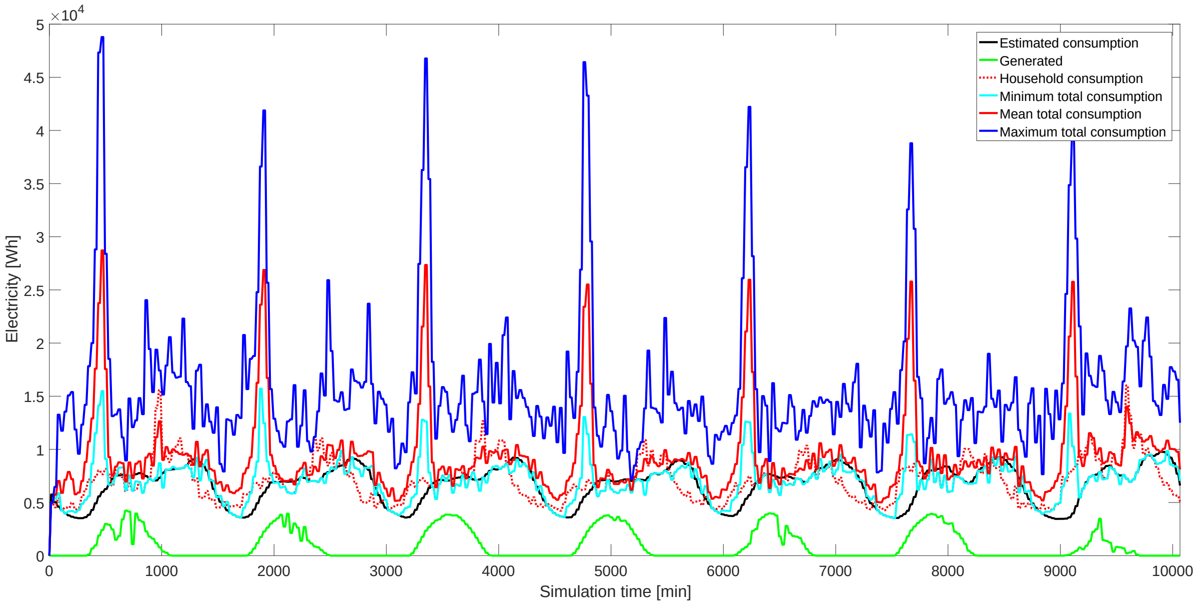


(b) Monte Carlo (N = 30) experiment of base scenario with local trading

Figure 5.3: Energy pattern plots for the base scenario Monte Carlo experiments

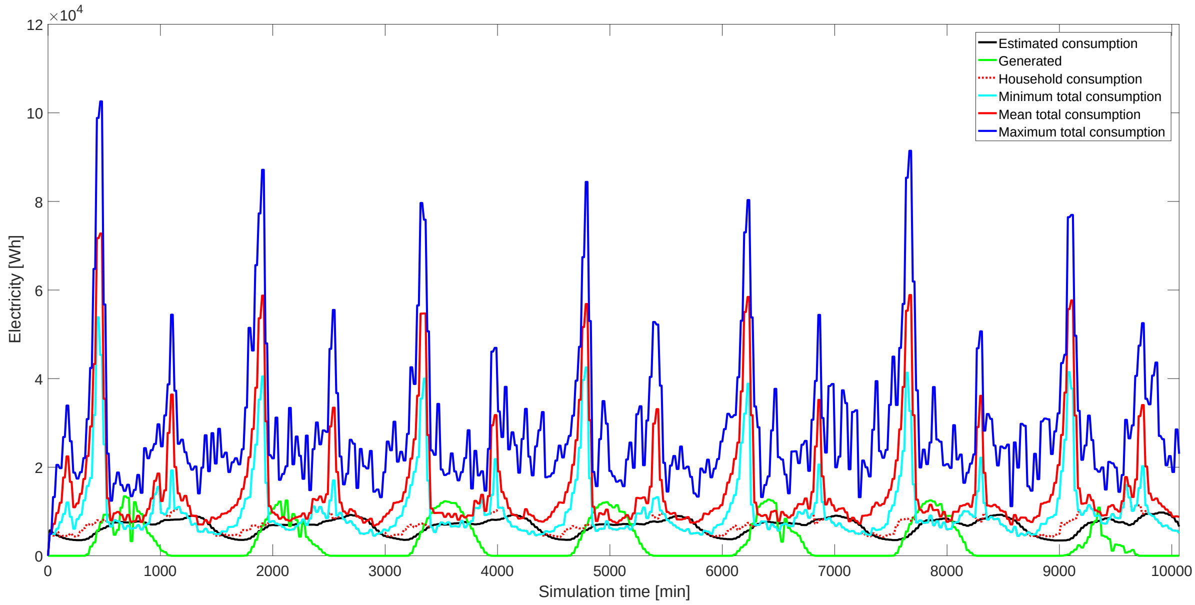


(a) Monte Carlo (N = 30) experiment of short term scenario

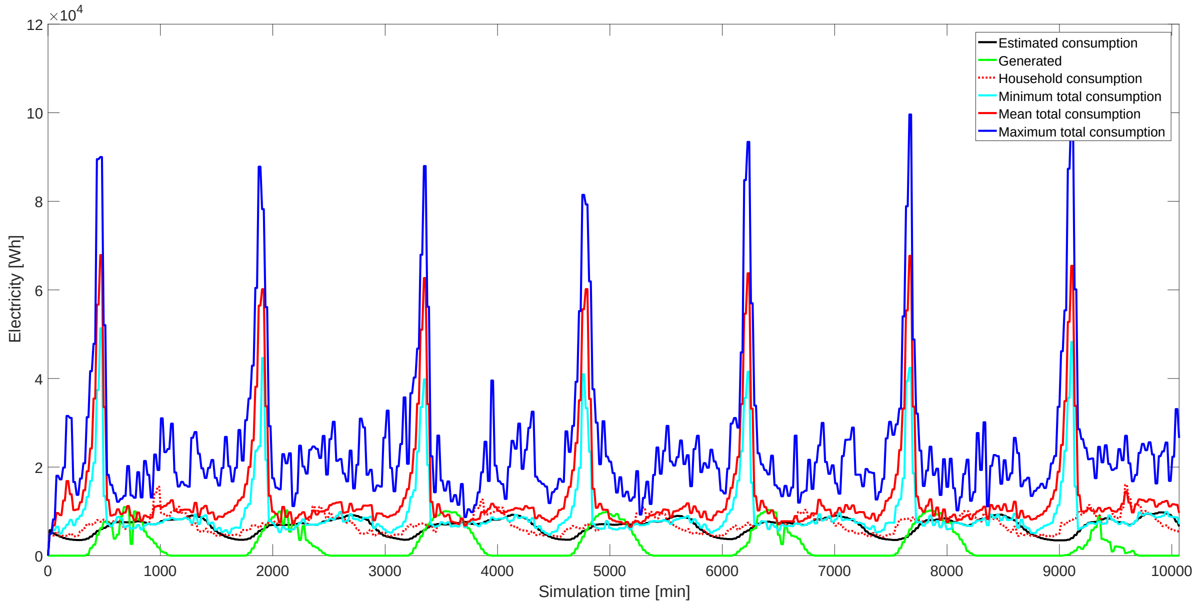


(b) Monte Carlo (N = 30) experiment of short term scenario with local trading

Figure 5.4: Energy pattern plots for the short term scenario Monte Carlo experiments

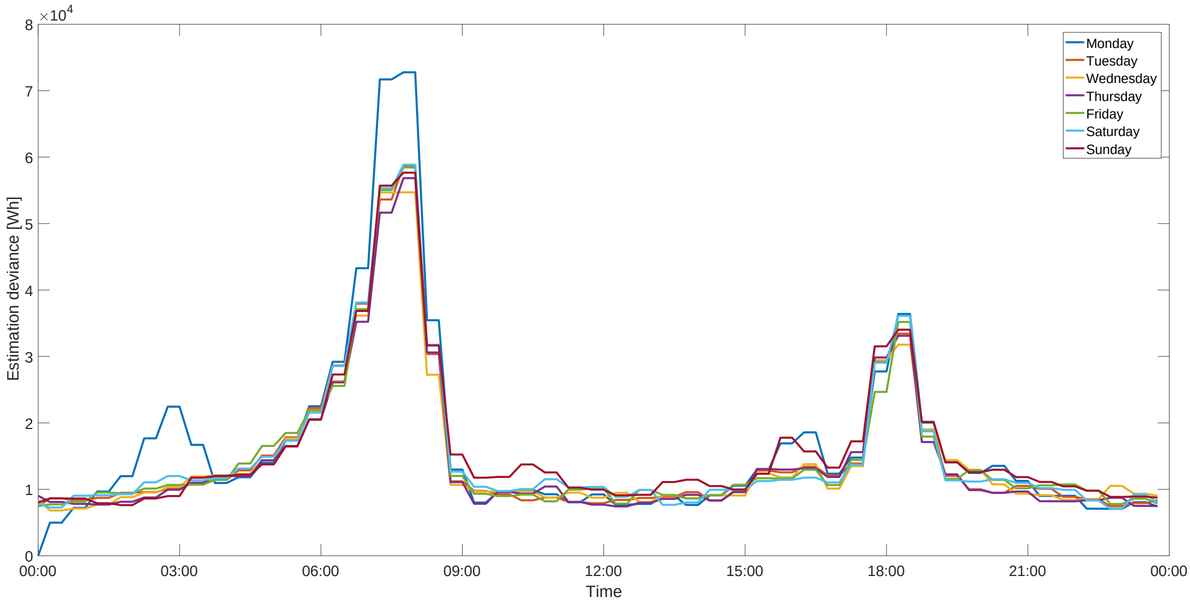


(a) Monte Carlo (N = 30) experiment of long term scenario

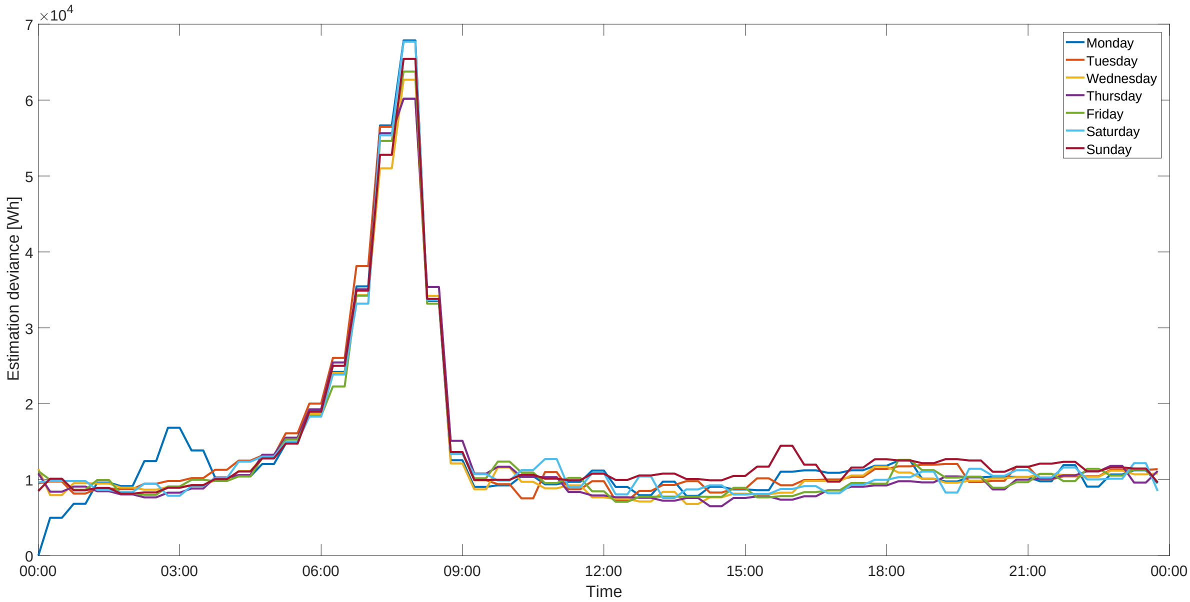


(b) Monte Carlo (N = 30) experiment of long term scenario with local trading

Figure 5.5: Energy pattern plots for the long term scenario Monte Carlo experiments



(a) Without local trading



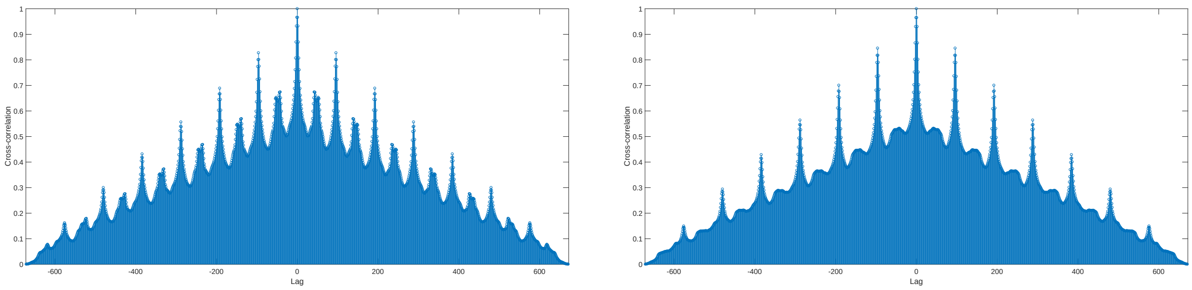
(b) With local trading

Figure 5.6: Deviation plots per day

Table 5.3: Independent samples t-test for equality of means

Scenario	Trade [Y/N]	Mean [Wh]	Std. Deviation [Wh]	T-test p value [-]	95% confidence interval
Base	No	7376	118.5	0.000	$7332 < \mu < 7421$
	Yes	7272	69.43	0.000	$7246 < \mu < 7297$
Short term	No	9698	467.7	0.000	$9524 < \mu < 9642$
	Yes	9298	358.0	0.000	$9164 < \mu < 9431$
Long term	No	15214	499.0	0.000	$15028 < \mu < 15400$
	Yes	13660	427.7	0.000	$13500 < \mu < 13820$

backed by the cross-correlation plots in Figure 5.7, where higher peaks are noticeable around $k * 100\lambda$ (a shift of 96 represents a shift of one day). When trading is enabled (Figure 5.7b) these peaks are slightly more pronounced than without trading (Figure 5.7a), being higher and narrower. Furthermore, in Figure 5.7a smaller cross-correlation peaks are visible between the larger peaks, signalling more noise. These sub-peaks disappear when local trading is enabled (see Figure 5.7b). In conclusion, not only does local trade improve grid stability, imbalances become easier more periodical and thus easier to predict.



(a) Without local trading

(b) With local trading

Figure 5.7: Cross-correlation plots for the mean deviance in the long term future scenario

5.2.2. Exploring the effects of grid size

From the validation tests presented Appendix B it can be concluded that the number of households has a profound influence on the balance in the grid and the required transactional throughput. The short term future is regarded as a feasible implementation horizon and will therefore serve as a base for experiments exploring the effects of grid size. As could already be concluded from the scenario analysis (presented in Section 5.2.1). the maximum deviations can be attributed to fixed times: just before noon. The experiments were designed test the influence of the number of households on the deviance between estimation and total grid consumption. Three experiments were designed using the short term future scenario (see Table 5.2), only varying the number of households uniformly between 107 to 10000 over 50 experiments. After each run the minimum, mean and maximum deviation is collected. Scatter plots and an unstandardised regression analysis will serve as predictors for scalability in terms of estimation deviance. Robustness of the proposed blockchain system is achieved if it can function under the worst of circumstances. Therefore, the throughput maximums and is collected after each run. To test if there is an equal division in market share, the minimum and maximum number of transactions over all PEVs will also be stored. The results will be analysed using unstandardised regression coefficients and used for the design presented in Section 5.3.

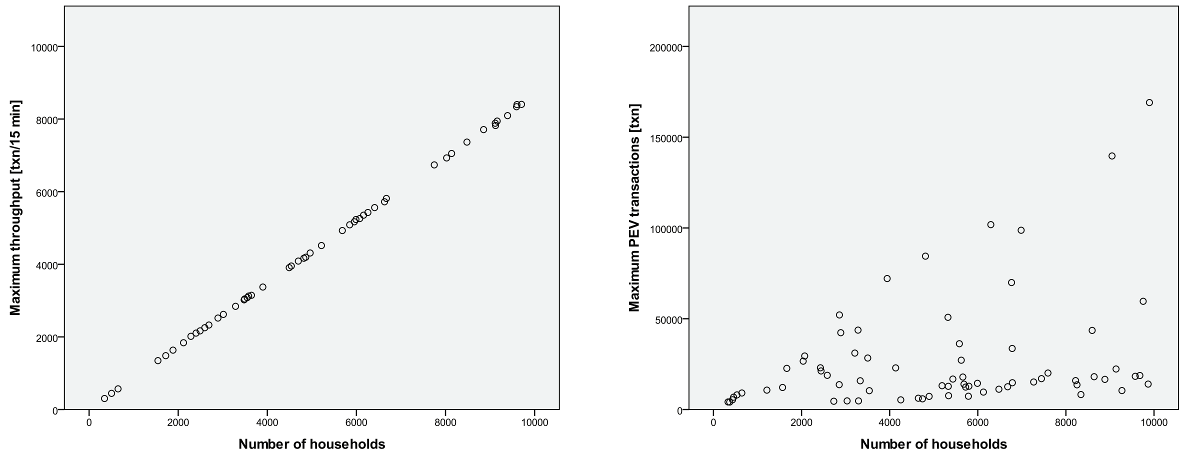
Figure 5.8 gives the scatter plots for the grid size tests. From Figure 5.8a it is evident that there is a very strong linear relation between the number of households and the maximum throughput. Actually, the R^2 statistic is equal to 1.00, signalling a perfect fit of the regression model

$$\hat{Y} = b_0 + b_1 * X_1, \tag{5.1}$$

giving

$$\text{Maximum throughput} = 9.209 + 0.866 * \text{Number of households}. \tag{5.2}$$

This means that with every increase in the number households an estimated 0.866 transaction is added to the maximum throughput, if the rest of the parameters is kept constant.



(a) The number of households on throughput (b) The number of households on max PEV transactions

Figure 5.8: Scatter plots for the number of households and transaction outputs

The relation between the number of households and the maximum number of PEV transactions is much weaker than the maximum throughput. This is apparent from Figure 5.8b, as the dots are more randomly dispersed. The R^2 statistic is only 0.027, showing that little of the variance in the maximum amount of PEV transactions can be explained by the number of households alone.

From Figure 5.9 it can be concluded that the deviance increases linearly with the amount of households. This is supported by the R^2 statistics 0.999 and 0.995 for the mean deviance, respectively maximum deviance. Equations 5.3 and 5.4 give the unstandardised regression equation for the mean, respectively maximum deviance. The minimum deviance is zero, this is because local trading perfectly matches estimation and consumption at certain points in each simulation run.

$$\text{Mean deviance} = 69 + 22.325 * \text{Number of households} \tag{5.3}$$

$$\text{Maximum deviance} = 8000 + 196.987 * \text{Number of households} \tag{5.4}$$

5.2.3. Financial implications for system users

The validation tests showed that there is a strong causal relation between the number of PEVs and the charging costs/profits associated with the system. Financial stimuli are important drivers for system participation. Moreover, the system needs to be tested on the allocation of cost and profits. Experiments were, as in Section 5.2.2, based on the short term future scenario described in Section 5.2.1. The fraction of PEVs was varied uniformly between 0.00 and 1.00, over 50 runs, to test the influence of the number of PEVs on the mean and maximum charging session costs, as well as the mean charging sessions earnings.

Figure 5.10 gives the resulting scatter plot. As can be seen the average charging cost per session is predominantly constant over the range over REG penetration ($R^2 = 0.612$), being only slightly negative: $b = -1.011$. This results in the following regression equation:

$$\text{Mean charging cost} = 2.124 - 1.011 * \text{PEV fraction}. \tag{5.5}$$

There is no significant effect on the maximum charging costs by the PEV penetration alone. This means that for users the costs do not change significantly if more PEVs are added, while the grid will benefit from more balancing capacity.

Through an independent samples t-test the effect of trading on financial indicators is tested. 30 runs of the short term future scenario are performed with trading and an equal number without trading, creating an output dataset with two groups. The null hypothesis is

$$H0: \mu_1 = \mu_2. \tag{5.6}$$

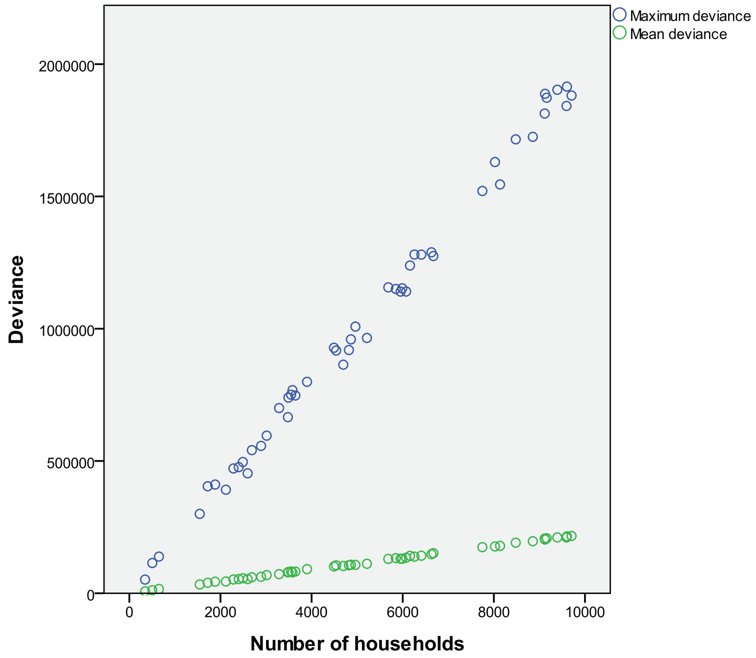


Figure 5.9: The number of households on the mean and maximum deviance

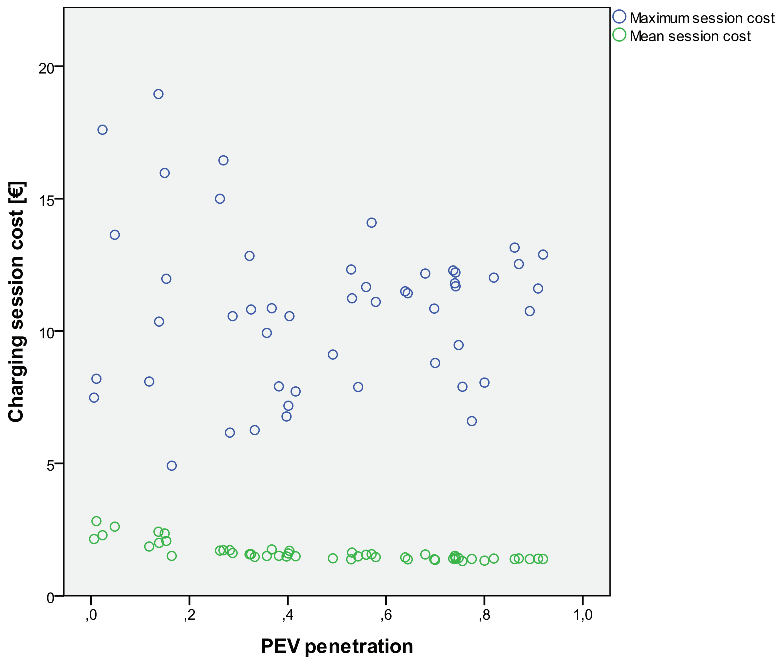


Figure 5.10: The PEV penetration rate on the mean and maximum charging costs

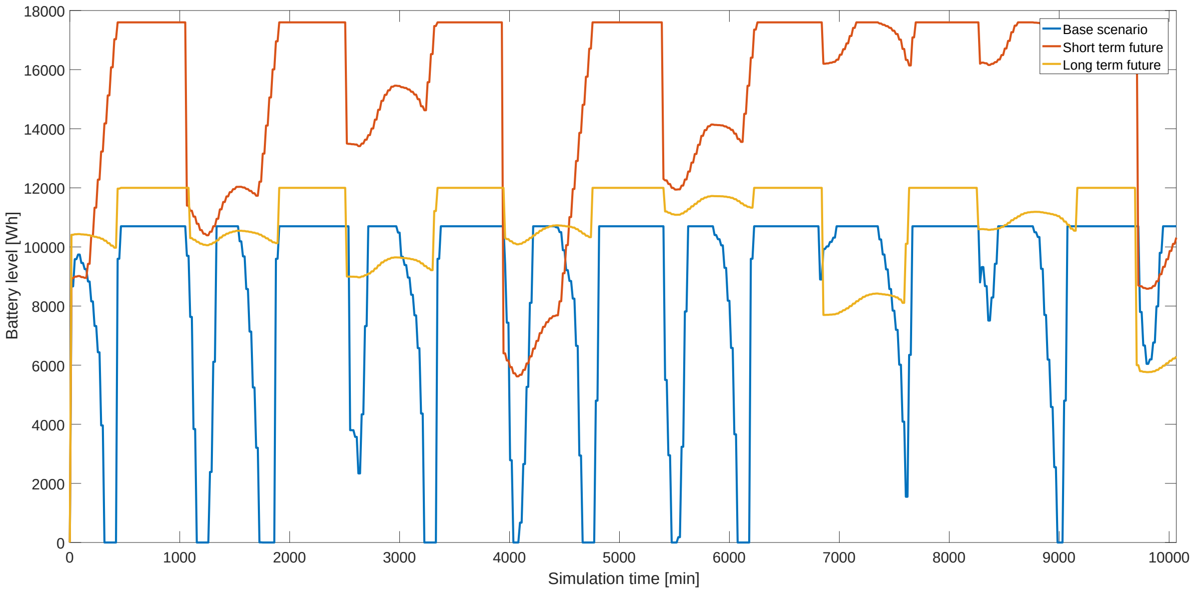


Figure 5.11: The PEV penetration rate on the mean and maximum charging costs

With a significance level α of 0.05 the alternative hypothesis

$$H1 : \mu_1 \neq \mu_2 \tag{5.7}$$

is tested for the mean and max charging sessions cost and mean charging session profit. The charging sessions earnings can not be analysed, as there are no earnings if trading is disabled. For all three financial outputs there is a significant change in sample means. The costs per charging sessions increase, with resulting net profits decreasing. Considering the nature of the input data this could be explained by the assumption of fixed tariff. The households participating in the pilot project that served as data source, were incentivised to move their generation from periods with high prices to time spans with low prices. This leads to underestimation at low prices and overestimation at high prices. Due to the trading algorithm this results in PEVs charging at high prices and discharging at low prices, resulting in the aforementioned cost relations.

5.2.4. The strain on PEV batteries

The SOC has an indirect link with the full-electric PEV (BEV) fraction and the number of public charging stations. As is assumed from the analysis presented Appendix B the BEV fraction influences the average battery capacity of PEVs in the model, which in turn affects the aggregated SOC curves. Based on the number of public charging stations, the average charging capacity power is expected to be a better predictor. These two statistics are collected for each of the 50 runs in an experiment wherein the BEV fraction was uniformly varied between 0 and 1 in the short term future scenario. A regression model is formulated where the two statistics serve as predictors for the minimum SOC.

Figure 5.11 shows three battery curves, one for each of the three simulation scenarios (see Table 5.2), of household-owned PEVs. The curves show a recurring pattern of maximum charge in a disconnected state, a sharp decrease at arrival and a game of charging and discharging between arrival and departure. The PEVs in the base, short term and long term curves had a battery capacity of 10.7, 17.6, respectively 12 kWh. With this in mind one can easily spot the difference in how much the battery level changes over one session. While in the base scenario the battery is fully emptied and recharged several times overnight, the curves in the future scenarios show much milder behaviour. This is a direct result of the number of PEVs available to the grid for balancing efforts. Spread out over a larger number of batteries, the impacts are less severe.

As can be seen in Figure 5.12 the assumption that the BEV fraction directly influences the average battery capacity holds for the model. The causal relation is significant, linear and strongly positive ($R^2 = 0.944$).

Figure 5.13 gives the scatter plots for the average battery capacity and charging power on the minimum SOC. As can be seen in Figure 5.13a there is no significant relation ($R^2 = 0.002$) between the average battery and the minimum SOC. The effect between the average charging power and minimum SOC is also insignificant (Figure 5.13b). This conclusion is backed by Figure 5.13c, showing a very narrow box plot of the mini-

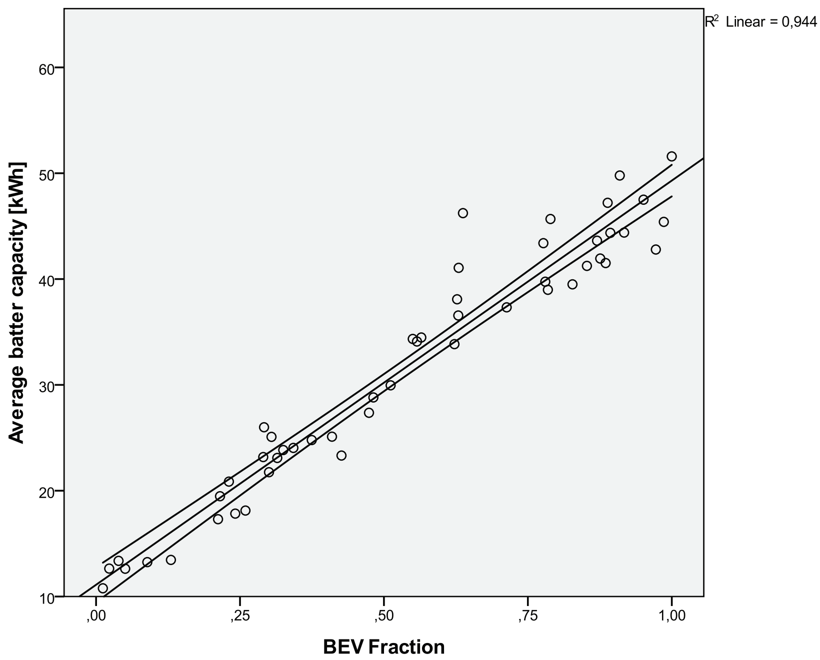
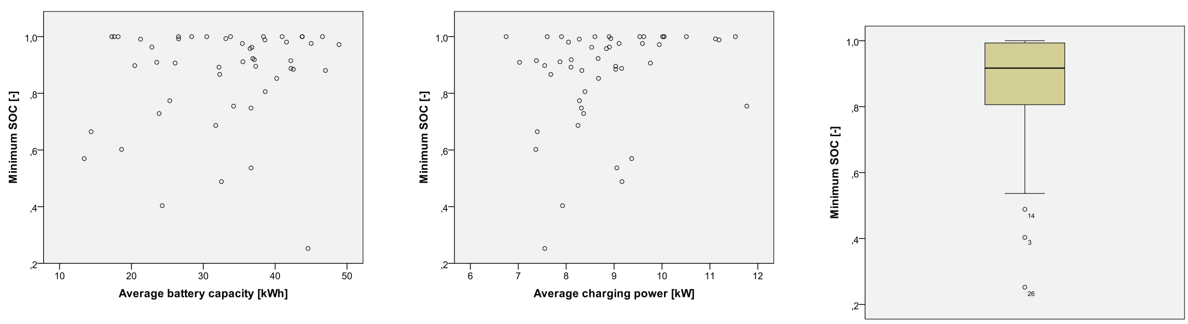


Figure 5.12: The BEV fraction on the average battery capacity

mum SOC. The average of the minimum SOCs in the experiment equals 0.866, thus the model can, to a large extent, safeguard battery level at departure. However, if we reflect on the outlier, case 26, the minimum SOC at departure during that run was 0.252. If that specific trip would be an emergency trip, for instance to the hospital, a low battery level might pose a problem for BEVs, as PHEVs have a ICE to fall back on. In The Netherlands the average distance between a household and the nearest hospital is 4.7 km [32]. According to [59] the average PEV uses 1 kWh to travel 5 km. In the worst case, travelling by Renault Twizy (hardly the emergency response vehicle), would result in a travelling range of $0.252 \times 6.1[\text{kWh}] \times 5[\text{km*kWh}^{-1}] = 7.6[\text{km}]$. Although this can be considered as successful in the worst case scenario, under different circumstances this might not hold (e.g. if hospitals are further away or in scenarios with less PEVs). Therefore, it is recommended to base minimum charge on absolute levels, rather than SOC, and offer the possibility for users to opt for different emergency trip scenarios and their likelihood. An eventual implementation could then automatically account for minimum battery level according to user preferences.



(a) Average battery capacity on minimum SOC

(b) The average charging power on minimum SOC

(c) Minimum SOC box plot (N = 50)

Figure 5.13: Scatter plots for the average battery capacity and charging power

5.3. Deploying with blockchain and reliability testing

The most important trade-off that has to be made when designing a blockchain is between scalability and performance. Scalability deals with the number of nodes taking part in the consensus algorithm, while performance is concerned with the amount of transactions that can be validated per time unit, or transactional throughput. Traditional proof-of-work (PoW) blockchains such as Bitcoin offer high scalability but poor performance. According to [40, 197] the peak throughput of Bitcoin is 7 transactions per second with small transaction sizes (so low information level). However, the network is operational on thousands of nodes spread out over the world.

Byzantine fault tolerant (BFT) algorithms have proven to reach much higher performance (tens of thousands transaction per second) at the cost of scalability. While BFT networks can serve up to thousands of clients, only up to 20 nodes (or servers) can partake in the consensus algorithm [197]. In addition, BFT blockchains are per definition permissioned, requiring the sharing of identities amongst the servers.

Looking at the intended implementation, permissioned blockchains are perfectly suited. A critical difference between the system described in this work and blockchain origins through cryptocurrencies like Bitcoin, is the entanglement with a physical infrastructure. On standard blockchains it is not the responsibility of the technology to provide accountability, whether or not this is desirable. The technologies build on trusting that the majority voting principles result in a valid transactional history, but offer no back-up or liability if things go awry. As a result, cryptocurrencies can remain highly anonymous. However, with electricity grids and other critical infrastructures, malicious behaviour on the underlying blockchain could result in failures on the physical infrastructure. Therefore, it must be possible to hold consensus servers accountable. Moreover, clients/users in the system must be traceable by authorities so taxes on grid use can be collected and trade can be verified with actual consumption and production.

The throughput observed in the model is given per 15 minute intervals. Nevertheless, the maximum throughput does not exceed 10,000 transactions per 15 minutes, let alone the tens of thousands per second that is feasible with practical BFT algorithms. Moreover, the maximum throughput in the model was caused by grid sizes in terms of households, exceeding the number of clients coverable by BFT consensus. Therefore, it is assumed that for the timescale of the current system, decentralised trading in smart grids can be facilitated by blockchains based on Byzantine fault tolerance.

In this section the system design is connected to a blockchain, to test the performance of a BFT algorithm as a facilitator of peer-to-peer energy trade. By analysing the network delay conclusions can be drawn about possible response times of the proposed design. For that purpose a blockchain test network was designed and presented in Section 5.3.1. The network was connected to a simulation run of the ABM, of which the results are presented in Section 5.3.2.

5.3.1. Blockchain test network architecture

Tendermint [176] was chosen as a blockchain platform, due to its foundation in BFT, interconnectivity with different programming languages, well-organised documentation and a pre-packaged test application. That test application is applicably called dummy application, as it simply accepts any transaction broadcast to the network. However, as the ABM already covers smart contract logic and resulting transactions are deemed valid, this is not considered a problem. In addition, the consensus algorithm provided by Tendermint is a full-fledged BFT algorithm so its applicability can be tested independent of transaction validation.

The network consists of two Linux virtual machines (VMs), hereafter referred to as CGI2 and CGI2. The VMs operate on an Ubuntu 4.4.0-47-generic OS, with an Intel®Xeon®E5-2673 v3 CPU @ 2.40GHz and 4 GB of RAM. The VMs are connected to the same (virtual) network and communicate on IPs 10.0.0.4 and 10.0.0.5 respectively, through ports 46656-46658.

The Tendermint application is installed using the guide presented by [177]. The prerequisites, Git and Golang, came pre-installed with the VMs. A directory was created for the Tendermint applications written in Go and was set as the `GOPATH` environment variable. The `bin` folder was added to the `PATH` variable to allow for easy execution of the applications:

```
~$ mkdir go
~$ mkdir go/bin
~$ echo export GOPATH=$HOME/go >> $HOME/.profile
~$ echo export PATH=$PATH:$GOPATH/bin >> $HOME/.profile
~$ source .profile
```

The Tendermint applications were then installed from source using the following commands:

```
~$ go get github.com/tendermint/tendermint/cmd/tendermint
~$ go get -u github.com/tendermint/abci/cmd/...
```

This grants access to the Tendermint node application (through the earlier set `$PATH`), as well as the dummy consensus application. In order for the network to work, the two VMs need to be added to the validator pool, such that they can partake in the consensus scheme (see Section 3.3). This is done by generating validator keypairs and adding the public keys to the genesis block, stored as .json file in the Tendermint root folder (`$HOME/.tendermint`). These actions are performed by running the following command lines on each VM:

```
~$ mkdir .tendermint
~$ tendermint gen_validator >> .tendermint/priv_validator.json
```

The genesis.json file is based on both public keys and added to the Tendermint root folder on both VMs. The public/private keypairs are generated using Ed25519 public-key signature system [189]. Each validator is given a weight, used to determine who gets to propose a new block for each round. This is set using the "amount" property, and assumed equal for both VMs. The "app_hash" represents the blockchains state at genesis and is thus empty. The contents of the genesis.json are as follows:

```
{
  "genesis_time": "2016-03-24T13:38:00.000Z",
  "chain_id": "chain-1",
  "validators": [
  {
    "pub_key": [
      1,
      "2F8B31FC36BBE42501119D0151682986B4A70B04FE13BE2FE2362743C294080F"
    ],
    "amount": 1,
    "name": "VM_CGI-1"
  },
  {
    "pub_key": [
      1,
      "5124119D307C795CA5FB4E75184E3172D2693F795C7250AFA7C619F0BF070DC4"
    ],
    "amount": 1,
    "name": "VM_CGI-2"
  }
  ],
  "app_hash": ""
}
```

The network is started by running the dummy app and a seeded Tendermint node on each VM. The applications are run remotely using PuTTY SSH with a total of four terminals, (one for each dummy app and one for each Tendermint node). The Tendermint node initialisation is seeded so the VMs know on which address to start communication. The command lines are (run in separate terminals):

```
~$ dummy
~$ tendermint node --seeds=10.0.0.4:46656,10.0.0.5:46656
```

Port 46656 is the application's API channel and used to communicate between node and consensus algorithm. Port 46657 is the used to listen for incoming transactions. The transactions are broadcast to the network using a Windows 10 laptop (Intel Core i7-3630QM CPU @ 2.40GHz, 6GB RAM), through the ABM model described in this chapter (see Figure 5.14). On start-up of the blockchain experiment, the model makes a SSH connection based on a predefined PuTTY profile for CGI1 using PLink [138]. A RSA keypair was generated and introduced on the server to allow for password-less SSH. The SSH session is created using the following Java code in AnyLogic:

```java
// only if blockchain experiment is running
if(Blockchain){
   try
   {
      // excetue plink from command line using preset CGI putty profile
      // store process in Main property "SSH"
      SSH = Runtime.getRuntime().exec("plink -load CGI");
      // collect all process streams into Main agent properties
```

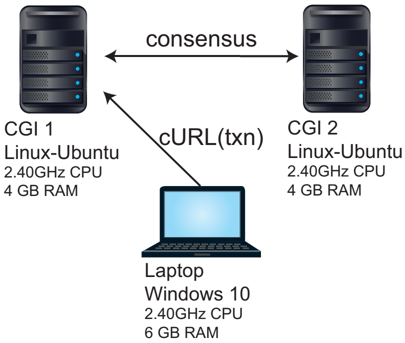


Figure 5.14: Graphical representation of the blockchain network

```
        SSHOut = SSH.getOutputStream();
        SSHIn = SSH.getInputStream();
        SSHErr = SSH.getErrorStream();
     } catch(Exception e)
     {
        System.err.print(e);
     }
  }
```

To mimic the one client-one connection relationship that would occur in real-life blockchain networks, only the transactions belonging to a randomly chosen household (either selling or buying) are added to the blockchain. Adding transactions is done through cURL, of which an example is given below:

```
~$ curl -s 'localhost:46657/broadcast_tx_sync?tx="
   10496=root.households952.pEV0,
   root.households62,345.0,
   -.005285686519999,
   0.0008260292606849"'
```

The transaction gets stored as a key-value pair, where the transaction number is taken as the key and the value is a hexadecimal representation of the concatenated string of the buying agent, selling agent, simulation time, transacted amount and transacted value. If the transaction is correctly broadcast a response from the blockchain is given:


```
{
   "jsonrpc": "2.0",
   "id": "",
   "result": [
      96,
      {
         "code": 0,
         "data": "",
         "log": ""
      }
   ],
   "error": ""
}
```


When designing the grid coverage of a blockchain network, system operators have control over the included number of houses with access to REG, the number of included public charging stations and the number of households. By varying these three input parameters and setting performance goals to minimise deviance and maximise SOC and profit, an optimisation experiment is formulated. Because the number of households negatively influences these KPIs, a minimum number of households is preferable. However, in accordance with opinions from smart grid experts at CGI Nederland B.V., the modelled grid size is set to 1000 households. For the remainder of the (static) parameter inputs, the short term future scenario is considered (see Table 5.2). The parameters of the blockchain experiment are presented in Table 5.4.

Table 5.4: Parameter values for the blockchain experiment

Parameter	Value
Car owners fraction	0.72
PEV owners fraction	0.25
REG owners fraction	0.238
BEV fraction	0.8
Public charging stations	17
Average occupancy	0.134
Number of households	1000

5.3.2. Blockchain test results

During simulation of the blockchain experiment, besides adding the transactions to the blockchain, they are also stored in a database. By comparing the transactions between the database and the blockchain, the reliability of blockchain as a energy market facilitator can be analysed. If a transaction was added to the blockchain can be verified through cURL:

```
~$ curl -s 'localhost:46657/abci_query?data="10496"&path=""&prove=false"'
```

Which results in a response from the servers a follows:


```
{
   "jsonrpc": "2.0",
   "id": "",
   "result": [
      112,
      {
         "response":
         {
            "index": 561,
            "value":
                "726F6F742E686F757365686F6C64733935322E704556302C726F6F742E686F757365686F6C6473363...",
            "log": "exists"
         }
      }
   ],
   "error": ""
}
```


The “log” property shows the transaction exists on the blockchain. The “value” property shows the hexadecimal representation (cut-off in the code listing above) of the transaction message

`root.households952.pEV0,root.households62,345.0,-0.005285686519999,0.0008260292606849.`

When repeating the verification process for the remaining transactions in the database, using the transaction number to cURL and checking the response log, it is found that all transactions that passed through the model have been successfully registered on the blockchain. In the console log it is shown that a block is added roughly every second:

```
NOTE[04-07|09:37:05] enterNewRound(8/0). Current: 8/0/RoundStepNewHeight module=consensus
NOTE[04-07|09:37:05] enterPrecommit: +2/3 prevoted proposal block. Locking
    module=consensus hash=64A842F2282E615C4F38A91FBF49505FE6ACCB93
NOTE[04-07|09:37:05] Finalizing commit of block with 7 txs module=consensus height=8
    hash=64A842F2282E615C4F38A91FBF49505FE6ACCB93
    root=169B82A96649827E5B50C82D42F6A4C8DFABC918
NOTE[04-07|09:37:06] enterNewRound(9/0). Current: 9/0/RoundStepNewHeight module=consensus
NOTE[04-07|09:37:07] enterPrecommit: +2/3 prevoted proposal block. Locking
    module=consensus hash=DC5905043CF847944F93C518F2DD97802FAE2F44
NOTE[04-07|09:37:07] Finalizing commit of block with 2 txs module=consensus height=9
    hash=DC5905043CF847944F93C518F2DD97802FAE2F44
```

```
    root=169B82A96649827E5B50C82D42F6A4C8DFABC918
NOTE[04-07|09:37:08] enterNewRound(10/0). Current: 10/0/RoundStepNewHeight module=consensus
NOTE[04-07|09:37:08] enterPrecommit: +2/3 prevoted proposal block. Locking
    module=consensus hash=4FC209F5F8136C277C91825B3E4096D089B9EB36
NOTE[04-07|09:37:08] Finalizing commit of block with 8 txs module=consensus height=10
    hash=4FC209F5F8136C277C91825B3E4096D089B9EB36
    root=169B82A96649827E5B50C82D42F6A4C8DFABC918
NOTE[04-07|09:37:09] enterNewRound(11/0). Current: 11/0/RoundStepNewHeight module=consensus
NOTE[04-07|09:37:09] enterPrecommit: +2/3 prevoted proposal block. Locking
    module=consensus hash=5374E13355004605F78F54376ACAF61B3081C2CE
NOTE[04-07|09:37:09] Finalizing commit of block with 2 txs module=consensus height=11
    hash=5374E13355004605F78F54376ACAF61B3081C2CE
    root=169B82A96649827E5B50C82D42F6A4C8DFABC918
```

Blocks contain a minimum of 0 and a maximum of 9 transactions. The strong linear relationship that was found between maximum throughput and the number households, leads to the assumption that the required throughput for this network would stay well under 10,000 transactions per second. With the maximum throughput of 10,000s transactions per second found in literature, performance is considered to be adequate. Although the model sends out transactions for a simulated period of 15 minutes, the effectiveness of adding multiple transactions per second of a single client's transactions is taken as a proof-of-concept for real-time energy markets based blockchain technology.

The blockchain on the two CGI VMs now contained an immutable record of the locally traded energy. Using the aforementioned cURL statement and converting the hexadecimal value to string, the total traded volume and associated costs can be found. Over one week the household is found to have traded 13.136 kWh, of which it sold 4.59 kWh and bought 8.77 kWh. The associated cost with buying a net 4.18 kWh is €1.82, leading to an average price of €0.44/kWh. This substantially higher than the normal rate (roughly €0.19/kWh), which is a result of the price plans that the input dataset had. This information, securely stored on the blockchain, could be used by market parties to bill, phasing out the need for reconciliation. If the capacity of the grid is incorporated in the trading logic, the system can also provide allocation automatically. The blockchain can then serve to pinpoint congested sections of the grid, allowing for crisp investments and thus higher efficient use of infrastructure.

6

Discussion and future work

The penetration of plug-in electric vehicles (PEVs) will become an important aspect of future energy systems. With both beneficial and harmful effects for electricity grids, smart management of their charging behaviour will become critical to the efficient use of both existing, and future infrastructure. If one places the increase of PEVs in the context of the energy transition, these realisations become even more important. Key to the energy transition is the decentralisation of energy systems, through the increase of distributed renewable energy generation (REG). Consumers become prosumers and expect to be able to feed any surplus of energy back to the grid. The resulting dynamics of decentralising grids will soon outrun the capacities of centrally-oriented market places. Local market places are considered to be an outcome and therefore this research focussed on the following research question:

How can electric vehicles promote energy transition and how can blockchain facilitate the decentralisation of future energy systems?

This chapter offers a step-back towards the research question, in Section 6.1, and provides an answer to it using the conclusions of the presented modelling study. It concludes with an outlook for the future and how certain assumptions could change and affect performance of an implementation in Section 6.2.

6.1. Discussion

In The Netherlands the energy system was designed from a central market's perspective. The liberalised market offers long-term contracts between producers and the largest of consumers. The remaining consumers are included in portfolios of balance responsible parties (BRPs), that represent an aggregated consumer pool on the central markets. BRPs bid on the day-ahead market based on expected energy consumption for the next day, which in turn is based on assumptions and generalisation. As a result, estimated consumption is different from actual consumption. Any imbalances have to be resolved by the BRPs on the much more expensive intra-day market. Using an agent-based model (ABM) it is shown that for a Dutch neighbourhood the required trade volume can amount to 24% of the total estimated weekly consumption. A lot of imbalance can be attributed to REG, as the Dutch energy system was designed in a pre-renewable era. Hence, not only does the centralised orientation lead to market inefficiencies, it can not account for REG, leading to unfair compensation for sustainable distributed generation (DG).

The rise of electric vehicles can be explained by the technological developments of recent decades. Namely, better performing power trains increased the driving range, resulting in rising attractiveness for consumers. Correspondingly, The Netherlands first saw a sharp increase in the number of plug-in hybrid electric vehicles (PHEVs) and later the rise of fully electric vehicles (BEVs). While, PEVs offer a better alternative than internal combustion engines (ICEs) in terms of the environment, their charging behaviour can increase the aforementioned balancing problems in decentralised grids. Using the ABM it was shown that, under the current circumstances, plug-and-charging of PEVs can increase a grid's demand with 61%. With a penetration of just 25%, feasible on the short term, peak demand can increase a grid's consumption with a staggering 357%. Reasonably, a lot of research focusses on peak mitigation, often shifting it to overnight when otherwise demand would be low. However, this is often results in a shift of the problem, not an actual solution

Table 6.1: Comparison of family situations in the model and The Netherlands

Dataset	Single person	Couple	Family	Other
Model	33%	40%	24%	4%
The Netherlands	37%	28%	26%	9%

for it. There have been efforts that try to control charging behaviour using a grid's smart communication capacities. Yet, the resulting algorithms are computationally heavy and incorrectly account for individual user preferences. They often required aggregators that would introduce yet another intermediary in an already complex system. Some work has been done on using PEV batteries as local storage, however they offer no practical solutions for tying together energy peers on a decentralised level.

Blockchain was introduced as a timestamping server in the Bitcoin network in 2008. The key attribute of blockchain is that it can rule out the need for intermediaries. By directly connecting producer and consumer, trading can speed up and occur at lower costs. Blockchain can offer the transparency and security that is desired by system users. Early blockchains were based on proof-of-work (PoW) consensus algorithm that required immense quantities of energy (Bitcoin's network consumes roughly the same as a country like Ireland) and long times for transaction finality (roughly an hour in the case of Bitcoin). For energy-based blockchain, consensus algorithms based on Byzantine fault tolerance (BFT) offer a much higher performance than PoW, at the cost of scalability. Research shows that BFT can facilitate a throughput that runs in the tens of thousands of transactions per second, whereas the throughput found in the model for an average Dutch neighbourhood stays well under 10,000 transactions per second.

The solution proposed in this work accounts for individual user, both PEVs and households, preferences and aggregates them to benefit decentralised grids on from system's perspective. A local trading algorithm was developed, based on blockchain, that tries to minimise the deviance between estimated and actual consumption, maximise user profitability and minimise imposing restrictions on usage patterns through retaining minimum state-of-charge. The algorithm has proven to decrease deviance by an average 1.4% in the current situation, 4.1% on the short term and 11% in the long-term future, with a respective PEV penetration of 1%, 25% and 80%. Moreover, with increasing PEV penetration the costs associated with charging decrease slightly. Finally, the algorithm safeguards the minimum state-of-charge at departure. However, in the current situation, with low PEV penetration, batteries are emptied and refilled multiple times during one sessions. The would imply that from a user's perspective there is a possibility of having an empty battery for an emergency trip. In order to avoid this, the algorithm should incorporate a minimum absolute battery level. In future scenarios, with higher PEV penetration, these harmful effects are no longer present. At around 80% REG penetration at 25% PEV penetration, PEV charging from REG starts to dominate and supersedes discharging in the network.

The simulation results presented in Chapter 5 clearly show that, without smart charging mechanisms, PEV will drastically decrease the stability of a grid's energy supply. The increases in load during PEV peak demand are severe and appear at random. As a result, balance responsible parties (BRPs) have no way of accounting for increases in load that can easily triple what was expected. The proposed solution not only decreases the imbalances in the grid, but also makes them more predictable. Therefore, BRPs and grid system operators can account for the demand peaks, occurring around 8:00 in the morning, and minimise their harmful effects.

The demographics of the households that were source to the smart metering data were known and compared to averages in The Netherlands. Gender-wise the sample closely matches the Dutch population: 46% men compared to 49% [27]. According to [30] the Dutch population has an average age of 41, compared to 37 in the pilot sample. Looking at the highest level of education 35% of respondents followed lower education, 50% middle education and 15% higher education. For the Dutch population these figures were 33%, 39%, respectively 28%. The sampled neighbourhood seems to have a higher share of people having followed middle education, taking away from the share of higher educated people. A comparison of the different living situations is given in Table 6.1. As can be seen the number of two-person households is substantially higher in the model than in the real-life situation. From [29] it can be concluded that the average Dutch household consists for 2.15 persons, quite similar to the average household participating in the pilot project: 2. It could not be deduced from the model datasetf if the unemployment data were given over all respondents or only over those belonging to the labour force, thus a comparison was not made.

While the demographics of the households used in the model, apart from education, do not differ significantly from the average Dutch population, the houses do. The pilot project was based on a neighbourhood consisting of houses build from a sustainability perspective. This means that measures were taken to increase efficiency and that the homes were designed for a sustainable future. Sadly, not all houses in The Netherlands were build this way. Therefore, if the modelling results are to be generalised to a larger scope (for instance The Netherlands), the conclusions from this study have to be tested against different input datasets. On top of that, the simulation data corresponds well with the average situation, giving no insights on performance under extreme circumstances, for instance areas with considerately lower income, or education. Furthermore, the conclusions apply only to smart grids, where decentralised communication - optionally to the appliance level - is possible. Since, the input data was collected from smart meters, the integrated set of model assumptions is based on the system's availability to a grid's state.

The algorithm was tested in combination with a small blockchain network, as a proof-of-concept for blockchain-based energy trade. The throughput resulting from the implementation lies well under the theoretical max of BFT algorithms. The tests that were performed indicate an average throughput of 3 transactions per second. Considering the linear relation between maximum throughput and the number of households, a feasible grid size would impose approximately 3000 transactions per second. The maximum throughput for such a grid will be less than 9000 transactions per second. The reliability of the technology is proven through verifying the occurrence of transmitted transactions on the blockchain. With a single household the reliability is 100%.

6.2. Future work

The implementation base of electric vehicles in combination with blockchain-driven smart grids was a natural choice considering the technological standards, in terms of intelligent communication, are generally high in PEVs. Moreover, the CEMS database provided a good starting point on demographic coverage. However, there is a lot of to be done if system operators are to be convinced of blockchain's full potential for energy systems. This section gives an overview of further research to extend this work, or to explore the implementation in other sub-systems.

Demographic coverage and user behaviour

The simulation results show that distributed smart grids can benefit from the balancing effect of PEV batteries. However, to investigate the effects under different circumstances grids from different areas in The Netherlands should be tested. By changing the input data, the conclusions from the model cover a larger demographic spread and as result the generalisability of results becomes more accurate. Possible collection methods could resemble that of the Jouw Energie Moment (JEM) project, or a grid that more closely follows the trends in the energy transition (for instance when looking at the availability of REG or the diversity of technologies such as adding wind turbines and heat pumps). Another approach is to focus at neighbourhoods with an extreme manifestation of demographic properties, such as poverty. Furthermore, if valid data is collected over a longer period of time, stochastic noise will reduce over the length of simulation runs. This would enhance the quality of results.

The ABM covers only home-work-home trips in the case of household-owned PEVs. By stochastically assigning departure and arrival times accordingly, the resulting charging behaviour offers a good start for scenario analysis, however doesn't fully capture real-life charging behaviour. In the real-life situation, a lot of EVs are used by stay-at-home mothers, driving children to-and-from school and household shopping. This would result in a lot more PEVs being available during the day on an interval basis, instead of only during the night. The performance of the proposed solution is highly dependant on the amount of PEVs simultaneously connected to the grid. While the behaviour will become more dynamic, i.e. plugging in and out more often, overall the algorithm could benefit from spreading out imbalances over a longer period and more local storage.

It is assumed in the model that all PEV owners partake in the system. If one considers the participation rate in the JEM project (roughly 70%), this assumption will not hold in real life. The penetrations of PEVs simulated in the model are therefore an underestimation of the penetration required to achieve the same benefits. To achieve a 25% PEV participation rate the actual PEV penetration has to be higher. Most of the scenario variables were based on plans of the national government. Their efforts to incentivise/discourage EV driving will prove an important factor for the success of the proposed solution. Currently the model implies that whenever a PEV user isn't driving he/she connects the PEV to the grid. Data is required on the charging behaviour of PEVs at private charging stations.

The hidden benefits of blockchain-driven smart grids

There are a number of factors that are not taken into account with in the model, but could have an effect on the performance of the proposed system. One of those factors is the automation of reconciliation efforts. In the current system reconciliation can only be done after the passed period of consumption. Deviations from ex-ante, fixed monthly tariffs, based on expected consumption, are settled after for instance a year has passed. The measurements used for reconciliation are often generalised over neighbourhoods and inaccurate, resulting in an overall obscure process from a user's perspective. By storing energy trade data on a blockchain, an immutable record is kept of all electricity consumed and generated, allowing for automatic and real-time billing.

Another factor is the decreasing need for investment in transmission networks. Local trade can solve imbalance at the consumer level. This means less capacity of long distance transmission lines is required. The investment costs required for maintaining transmission network have not been examined in this study, but are expected to have an effect on the overall performance.

One of the assumptions in the model was that all transactions happen at the respective market prices, regardless of services offered. Dynamic pricing could result in financial benefits from a user's perspective. Taxes could be set to match relative capacity usage, benefiting distribution system operators (DSOs). How high these benefits could be and at what cost for whom is a possible topic of future research.

These, and possibly other, factors could be assessed using for instance cost-benefit analysis. The results of such a study could result in the first-ever financial framework for blockchain in utilities.

Redefining the Dutch electricity market

The solution offers TenneT (the Dutch transmission system operator, or TSO) a secure means for delegating balancing responsibilities. In the future, distribution grid operators (DGOs) could evolve into distribution system operators (DSOs), aligning with the movements of the energy transition. Grids of the future will feature a high penetration of REG, and in order to maintain stabilised grid frequencies, local storage is essential. PEVs have proven to be a feasible source of local storage and could be used by DSOs for frequency control. Under the assumption of local trade, DSOs will have a quick, immediate response to local network fluctuations, by using PEVs as primary reserve. By balancing not only on local blockchains, but also between them, the second reserves can be filled by facilitating exchange between neighbouring sub-grids. Local trading causes less uncertainty about the demand peak time of PEV charging, thus DSOs can more accurately dispatch other (distributed) resources to fill up the tertiary reserve. In the current state, the TSO is responsible with buying these services for the entire grid, often relying on big (unsustainable) generation plants. By shifting this responsibility towards DSOs, even household prosumers get a fair market share, as local sport markets for ancillary services, based on consumer/prosumer bid systems, become a real possibility.

Blockchain is said to have a highly disruptive character, reshaping markets where it emerges. The same is expected to hold for electricity markets. By enabling local trade and trusting in cryptography, rather than commercial intermediaries, currently existing market parties could be forced to adapt or even cease to exist. This is likely to start with electricity providers and metering companies. When electricity can be sold directly from generator to consumer, there is no reason for entities "providing" electricity. Moreover, as smart meters become abundantly available and reconciliation can be safely automated, metering companies will lose value as component in the value chain. For these market parties different roles can be invented, such as providing consensus server, of which the commercial feasibility is debatable. It is more likely that current market roles facing redundancy find services to offer in the new system, for instance in maximising profits for users at a commission base.

The initial investment costs of implementing blockchain in novel markets are expected to be considerable. As a result, there is an disadvantage for the first mover. Late movers could capitalise on this by freeriding on the first investment, while enjoying the same variable costs. This could lead to market fragmentation. In order to avoid competitors from benefiting from investments, companies could choose to centrally govern blockchains covering parts of the energy system. This would move away from the decentralising values of blockchain. In such a case the benefits would decrease from a system user's perspective.

The purpose of this work was to facilitate the shift from central to decentralised energy systems. Nevertheless, with the proposed architecture only one blockchain was covered. It will be interesting to see how one blockchain could communicate with others, moving balances from the neighbourhood level, to city (block) level, municipalities, countries and even continents. The result would be an interconnected network of blockchains, targeting grid problems from the bottom up, with market participation of the smallest of consumers. How the latencies would propagate and how connecting multiple blockchains would affect inter- and intra-performance and scalability is an interesting topic for future research.

Technological drivers

In the trading algorithm it was generalised that all charging infrastructure allows for reverse flow, i.e. has vehicle-to-grid (V2G) capabilities. While, the Dutch infrastructure is being equipped with the necessary tools to do so, this assumption currently does not hold. Without V2G an important balancing effect is diminished and the proposed solution could prove less useful considering the current state-of-the-art of charging infrastructure. As the coverage of V2G-ready infrastructure increases the debate on how V2G can be incorporated in grid system operations becomes more pressing. The solution implies that grid operators have to have an infrastructure that is ready for reversed flow.

Advances in battery technology will not only result in bigger, more efficient batteries, but also the emergence of new battery technologies altogether. Especially the introduction of supercapacitors could impose huge benefits to energy systems, offering bigger capacity, quicker response and more efficient conversions. The service level that PEVs could offer to distributed grids could become significantly higher. If this development is combined with battery swapping and/or the introduction of financially attractive static household storage, decentralised grids could become self-sufficient. With a electricity grid consisting of a large number of distributed, energy neutral networks resilience is increased. With such a grid the investment in REG could become less risky from a household's perspective, seeing there will be fair compensation for every generated unit. With decentralising system control the need for AC networks fades, allowing for more efficient local DC networks.

Blockchain as a contract mediator

It was already mentioned under the previous header that some market parties could face reshaping or, in extreme cases, extinction. It is realised that these changes cannot occur overnight, and will require gradual, step-wise implementation. One aspect that could help in the steady adoption of blockchain is the introduction of a blockchain-based contract ledger. CGI Nederland B.V. was closely involved with developing the C-AR, The Netherlands' central database of grid connections. Due to its properties of irreversibility, security, transparency and privacy, blockchain is perfectly suited to host contract data. It is imaginable that contracts move from supplier to supplier in a cryptocurrency-like manner. It is even possible to use the better established proof-of-work consensus algorithms, as performance is not critical - looking at the current time it takes to switch supplier - and energy suppliers are automatically incentivised to conduct in mining efforts.

A future research agenda

Based on the aforementioned areas of future research the following future research agenda is envisioned:

1. The current model can be expanded to incorporate REG from other sources. Solar energy is presently the only renewable energy source (RES) in the model, however The Netherlands has a relatively high share of wind and geothermal energy. By incorporating more distributed resources (DRs) the beneficial effects of the algorithm can increase.

2. Although different blockchain consensus styles came under scrutiny in this research, a comparison of different blockchain platforms was not conducted. Blockchain is still a novelty technology and considered a hype in many circles. If a solution is ever to be implemented, policy makers have to convinced of at least the technology's security and performance in an utility context. The maturing of the technology is currently being hindered by vast market segmentation. A company such as CGI could benefit from a detailed study on different platforms and conveying a standardised platform as solution base. The business logic in the model should then be translated to a smart contract layer.

3. A crucial aspect left out in the current work are the hardware requirements for running a blockchain client. If the technology would be able to run on smart meter technology, blockchain could be implemented together with the roll-out of smart metering infrastructure. Smart meters form the primary input of data to the system, an implementation there seems only logical. Another important implementation area is public charging stations. The technological state-of-the-art of these infrastructures should be leading in choosing a standardised blockchain platform.

4. The solution only operates under the assumption of system user participation. A thorough cost-benefit analysis should pinpoint the financial incentives required to activate users into using the system. Be-

sides financial incentives, environmental arguments are an important motivator for participation in local energy markets. Questionnaires, similar to those used for the JEM project, could shed a light on feasible participation and the corresponding implications for system performance.

5. If the solution proves useful from a client's perspective, an interface between blockchain and user has to be developed. The system is capable of combining individual user preferences from thousands of clients. However, the right balance between user input and system complexity has to be found.

6. With a standardised blockchain platform as starting point, policy makers can be approached for a demo project. In The Netherlands such pilot projects, e.g. the JEM project, are possible with up to 10,000 households according to experts at CGI. If in phases pilots move from intra-neighbourhood trading, to inter neighbourhoods, inter-cities, etc. trading, the technology's benefit for a nation-wide system could be proven.

7 Concluding remarks

This thesis covered the effects of electric vehicle charging on decentralising smart grids and the opportunities for blockchain-based local energy trade. An agent-based model of a smart grid was developed to implement and test an energy trading algorithm. The local trading algorithm was based on the principles of blockchain.

Current state-of-the-art electric vehicle charging is found to have a profoundly disruptive effect on decentralised grids, increasing prevailing peak demand and causing network congestion. However, when charging behaviour is aligned with the needs of the grid, the batteries of electric vehicles can be used as distributed resource to provide ancillary services. The developed algorithm is capable of exposing the benefits of an electric vehicle fleet to grid system operators, while still taking the user preferences of the individual owners into account. Consequently, with growing shares of electric vehicles the algorithm can provide primary frequency control, matching local generation and load.

By using blockchain as a market facilitator, trust is shifted from commercialised third parties into mechanisms of cryptography. As a result, trade becomes transparent and efficient and everyone gets a chance to participate on the market. Local markets will give a fairer compensation for distributed resources and in turn encourage individual investment. Collectively, consumers can have a much larger impact on the environment than (local) governments and businesses alone, if correctly incentivised. With the proposed solution, user cost-effective distributed renewable energy generation becomes a reality.

Although the current Dutch energy system is not ready for local trade, the proof-of-concept for blockchain-based energy markets in this work is a first step towards acceptation by governments. With proven feasibility, the technology is ready to be adopted for broader implementation into the electrical utilities sector. Blockchain allows for a leaner and more transparent energy system.

A
Agent-based model specification

This appendix gives an overview on the model specification and agent logic that was used to simulate a smart grid. The model was built in AnyLogic, a modelling tool supporting agent-based, continuous and discrete event simulations. While the model used in this research is completely based on the agent-based part, the simulations are based on discrete event principles. The code excerpts found in this chapter are written in Java, AnyLogic's native programming language. For any functionality that isn't native to Java or build for the purpose of the model, the reader is referred to the user manual of AnyLogic [6].

A.1. Aggregator agent

Within the aggregator agent, the trading algorithm is effectuated. For each time step the algorithm sets allocation for households and connected PEVs:

```
// used to determine throughput
previousNumberOfTxns = get_Main().Transactions.size();
// clear everything from last simulation step
SubSet.clear();
supplierPEVs.clear();
consumerPEVs.clear();
supplierHouseholds.clear();
consumerHouseholds.clear();
double estimation = 0.0;
double consumption = 0.0;
double generation = 0.0;
double allocation = 0.0;

if(PEVs.size() > 0 && time() < 10065){
   // real time trading is simulated by using actual time
   // rather than having to rely on predictions
   // simulates the (near) real-time responsiveness of blockchain technology
   double predictionScope = time();
   // iterate of households and get energy patterns
   for(Household h : get_Main().households){
      EnergyPattern eP = get_Main().getEnergyPattern(predictionScope, h);
      double hEstimation = eP.Estimated;
      estimation += hEstimation;
      double hConsumption = eP.Consumed;
      consumption += hConsumption;
      double hGeneration = eP.Generated;
      generation += hGeneration;
      // if a household has net production add it to the supplier subset
      if (hGeneration > hConsumption) {h.transactionAmount = hGeneration -
          hConsumption;supplierHouseholds.add(h);}
      // else if the household caused underestimation add it to the consumer subset
```

```
   else if (hEstimation < hConsumption) {h.transactionAmount = hConsumption -
       hEstimation;consumerHouseholds.add(h);}
}

// the energy balance is calculated from the household estimation, consumption and
    generation
// in the model postive energy means charging (overestimation)
// negative means discharging (underestimation)
// thus consumption is substracted from estimation
// only the surplus generation is added to the balance
// the rest is assumed to be used up by the respective households
energyBalance = estimation - consumption + Math.max(0, generation - consumption);

if(get_Main().smartCharging){ // iff smart charging is enabled
   ListIterator<PEV> litr = PEVs.listIterator(); // an interator of all plugged-in PEVs
   if(energyBalance > 0.0){ // overestimation (estimation > consumption and/or surplus) -->
       EV charge
      while(litr.hasNext()){ // foreach loop over all plugged-in PEVs
         PEV p = litr.next(); // select next PEV p
         // check if p requires energy
         // add p to aggregators working set if complies
         // else disable smartcharging on p
         if(p.batteryLevel < p.batteryCapacity) {SubSet.add(p);}
         else {p.smartCharging = false;}
      }
      if(SubSet.size() > 0){
         // every PEV gets an equal share of available energy
         allocation = energyBalance / SubSet.size();
         litr = SubSet.listIterator();
         while(litr.hasNext()){
            PEV p = litr.next();
            // add allocation (to the already allocated REG energy)
            p.chargingPowerPeriod = Math.min(allocation, p.powerInput / 4);
            // prevent charging power over outlet capacity
            p.chargingPowerPeriod = Math.min(p.powerInput / 4, p.chargingPowerPeriod);
            p.smartCharging = true;
         }
         consumerPEVs = SubSet;
      }
   } else {
      while(litr.hasNext()){
         PEV p = litr.next();
         p.smartCharging = false;
      }
   }
}
if(get_Main().v2G) { // iff V2G is enabled discharging can occur
   ListIterator<PEV> litr = PEVs.listIterator(); // an interator of all plugged-in PEVs
   if(energyBalance < 0.0) { // underestimation (estimation + surplus < consumption) -->
       PEV discharge
      while(litr.hasNext()){ // foreach loop over all plugged-in PEVs
         PEV p = litr.next(); // select next PEV p
         // check if p has energy left to discharge
         if(p.batteryLevel > 0.0) {
            SubSet.add(p); // add to working set of aggregator
         } else {
            p.discharging = false;
         }
      }
      if(SubSet.size() > 0){ // if aggregator has PEVs to work with
         // available energy is equally shared amongst PEVs
```

```
            allocation = energyBalance / SubSet.size();
            litr = SubSet.listIterator();
            while(litr.hasNext()){
               PEV p = litr.next();
               p.chargingPowerPeriod = Math.max(allocation, -p.powerInput / 4);
               p.discharging = true;
               if(p.inState(PEV.Discharging)) p.energyConsumption = p.chargingPowerPeriod;
            }
         }
         supplierPEVs = SubSet; // duplicate working set
         //System.out.println(Double.toString(time()) + "," + Double.toString(energyBalance) +
             "," + Double.toString(allocation));
      } else {
         while(litr.hasNext()){
            PEV p = litr.next();
            p.discharging = false;
         }
      }
   }
   // only trading between PEVs and Households
   if(consumerPEVs.size() > 0 && supplierHouseholds.size() > 0){
      // filled with smart charging PEVs: chargingPowerPeriod > 0.0
      ListIterator<PEV> cPs = consumerPEVs.listIterator();
      // filled with Households generation > consumption: transactionAmount > 0.0
      ListIterator<Household> sHs = supplierHouseholds.listIterator();
      // iterate over PEVs
      while(cPs.hasNext()){ // outer loop (PEVs)
         PEV cP = cPs.next();
         if(cP.smartCharging == false && cP.charging == false) continue;
         double demand = cP.chargingPowerPeriod; // > 0.0
         while(sHs.hasNext() && demand > 0.0){ // inner loop (households)
            Household sH = sHs.next();
            double supply = sH.transactionAmount; // > 0.0

            // create new instance of transaction class
            // and set properties
            Transaction txn = new Transaction();
            txn.Amount = Math.min(supply, demand); //in Wh
            txn.Buyer = cP;
            txn.ModelMinutes = predictionScope;
            txn.Seller = sH;
            txn.Value = sH.transactionAmount / 1000 *
                cP.getPeriodPrice((int)predictionScope).PriceTotal;
            get_Main().Transactions.add(txn);
            cP.Transactions.add(txn);
            sH.Transactions.add(txn);

            // check if blockchain experiment is running if so add txn to blockchain
            // household 63 was randomly chosen as the transaction source, because
            // the laptop running the model couldn't keep up with the throughput
            // of the entire model and SSHing it to the VM (CGI1), therefore
            // one client was chosen, agreeing more with a real-life situation anyway
            // one client connection per household/PEV/etc.
            if(get_Main().Blockchain) if(sH.getIndex() == 62){
               addTxnToBlockchain(txn);
               // try add transaction to database
               try
               {
                  addTxnToDb(txn);
               } catch(Exception e)
               {
```

```
            System.out.println(e.toString());
         }
      }

      // debug lines, should never be printed
      if(demand - txn.Amount < 0) System.out.println("Too much energy bought by " +
          cP.toString());
      if(supply - txn.Amount < 0) System.out.println("Too much energy sold by " +
          sH.toString());

      // the current PEV's (outer loop) demand is decreased with the transacted amount
      // or set to zero if demand is fulfilled
      demand = Math.max(0.0, demand - txn.Amount);
      // the current households's (inner loop) supply is decreased with the transacted
      // amount, or set to zero if the full supply is allocated
      sH.transactionAmount = Math.max(0.0, sH.transactionAmount - txn.Amount);

      // if the current household (inner loop) has allocated its supply
      // remove it from the working set as to continue with next household
      if(sH.transactionAmount == 0.0) sHs.remove();
      // if the PEV (outer loop) has filled its demand
      // break the inner loop (household) and continue with the next PEV
      if(demand == 0.0) break;
    } // inner loop (households)
  } // outer loop (PEVs)
} // end of conditional tag (supplier households and consumer PEVs)

if(supplierPEVs.size() > 0 && consumerHouseholds.size() > 0){
  // filled with discharging PEVs: chargingPowerPeriod < 0.0
  ListIterator<PEV> sPs = supplierPEVs.listIterator();
  // filled with Households estimation < consumption: transactionAmount < 0.0
  ListIterator<Household> cHs = consumerHouseholds.listIterator();
  // iterate over PEVs
  while(sPs.hasNext()){
    PEV sP = sPs.next();
    // fail-safe check
    if(sP.discharging == false) continue;
    double supply = sP.chargingPowerPeriod; // < 0.0
    while(cHs.hasNext() && supply < 0.0){
      Household cH = cHs.next();
      double demand = cH.transactionAmount; // < 0.0

      // create new instance of transaction class
      // and set properties
      Transaction txn = new Transaction();
      // household demand is calculated consumption - estimation
      // there is underestimation, thus consumption > estimation
      // demand is positive, hence inversely used here
      txn.Amount = Math.max(supply, -demand); // in Wh
      txn.Buyer = cH;
      txn.ModelMinutes = predictionScope;
      txn.Seller = sP;
      txn.Value = Math.abs(cH.transactionAmount) / 1000 *
          sP.getPeriodPrice((int)predictionScope).PriceTotal;
      // add transaction to total and
      // household agent transactions and
      // PEV agent transactions
      get_Main().Transactions.add(txn);
      cH.Transactions.add(txn);
      sP.Transactions.add(txn);
      if(get_Main().Blockchain) if(cH.getIndex() == 62){
```

```
                addTxnToBlockchain(txn);
                // try add transaction to database
                try
                {
                   addTxnToDb(txn);
                } catch(Exception e)
                {
                   System.out.println(e.toString());
                }
             }

             // debug lines, should never be printed
             if(supply - txn.Amount > 0) System.out.println("Too much energy sold from " +
                 sP.toString());
             if(-demand - txn.Amount > 0) System.out.println("Too much energy bought by " +
                 cH.toString());

             supply = Math.min(0.0, supply - txn.Amount);
             cH.transactionAmount = Math.min(0.0, cH.transactionAmount - txn.Amount);

             if(cH.transactionAmount == 0.0) cHs.remove();
             if(supply == 0.0) break;
          }
       }
   } // end of conditional tag (supplier PEVs and consumer households)

}
// add time step's throughput to overall throughput histogram
get_Main().transactionThroughput.add(get_Main().Transactions.size() - previousNumberOfTxns);
```

If a blockchain experiment is run, a SSH connection is open (see Section A.4). The transaction is then added to the blockchain using the `addTxnToBlockchain(Transaction transaction)` function (`void`):

```
// try add transaction to blockchain through ssh terminal
try
{
   // build UNIX compatible string from Transaction object
   // each transaction gets a number for later reference
   // and blockchain transaction verification
   String txnNr = Integer.toString(get_Main().Transactions.size());
   String txnString = txnNr + "=" + transaction.toString();
   txnString = txnString.replace("Seller = ", "");
   txnString = txnString.replace(" Buyer = ", ",");
   txnString = txnString.replace(" ModelMinutes = ", ",");
   txnString = txnString.replace(" Amount = ", ",");
   txnString = txnString.replace(" Value = ", ",");
   txnString = txnString.replace("[", "");
   txnString = txnString.replace("]", "");
   txnString = txnString.replace(" ", "");

   // An SSH connection is made to the first CGI VM in startup of Main
   // Transaction can be added to the blockchain using cURL on port 46657
   String SSHString = "curl -s 'localhost:46657/broadcast_tx_sync?tx=\"" + txnString + "\"'\n";
   int value = 0;

   get_Main().SSHOut.write(SSHString.getBytes());
   get_Main().SSHOut.flush();

   // used to log SSH terminal output to Console window
   Thread.sleep(1);
   if (get_Main().SSHIn.available () > 0) {
```

```
        value = get_Main().SSHIn.read ();
        System.out.print((char)value);

        while (get_Main().SSHIn.available () > 0) {
            value = get_Main().SSHIn.read ();
            System.out.print((char)value);
        }
    }
    if (get_Main().SSHErr.available () > 0) {
        value = get_Main().SSHErr.read();
        System.out.print((char)value);

        while (get_Main().SSHErr.available () > 0) {
            value = get_Main().SSHErr.read ();
            System.out.print((char)value);
       }
   }  // end SSH logger
} catch(Exception e)
{
   System.err.print(e);
}
```

A.2. Charging station agent

Each time step, charging stations calculate the possibility of the arrival of a PEV:

```
// if and only if no connected PEV
// trial-and-error resulted in expression
// with too many occupied stations occupancy would spike in the beginning
// and remain unoccupied for the remainder
if(hasCar == false && get_Main().chargingStations.NOccupied() <= 1){
   if(get_Main().chargingStations.average("occupancy") < get_Main().avgOccupancy){
      // coin flip based on average occupancy input param.
      if(bernoulli(get_Main().avgOccupancy) == 1){
         // set variable so agent can transition
         this.hasCar = true;
      }
   }
}
if(time() > 0.0) this.occupancy = this.occupiedMinutes/time();

pevConsumption = pEV.sumConsumption();
```

When a PEV connects, its sojourn time is stochastically assigned based on its charging type:

```
while(p.idleTime >= p.sojournTime){
   switch(p.chargingType){
      case "ParkToCharge":
         p.sojournTime = beta(45.7, 339.7, 0.02, 23.91)*60;
         p.idleTime = beta(7.3, 237.5, 0, 23.66)*60;
      break;
      case "ChargeNearHome":
         while(p.sojournTime < 0.02*60 || p.sojournTime > 23.99*60){
            p.sojournTime = logistic(1.9, 13)*60;
         }
         p.idleTime = normal(0, 23.53, 9.8, 4)*60;
      break;
      case "ChargeNearWork":
         while(p.sojournTime < 5.0*60 || p.sojournTime > 18.52*60){
            p.sojournTime = logistic(5.8, 8.7)*60;
```

```
        }
        while(p.idleTime < 0.0 || p.idleTime > 15.54*60){
           p.idleTime = logistic(1, 5.4)*60;
        }
     break;
     default: System.out.println("Charging type failed for " + this);
   }
}
```

A.3. Household agent

Household agents are generated from the CEMS database. On agent start up, its parameters are set using Bernoulli draws based on input parameters:

```
hasCar = bernoulli(get_Main().carOwners) == 1;
if(hasCar){
   hasPEV = bernoulli(get_Main().pevOwners) == 1;
   if(hasPEV){
      hasCar = false;
      add_pEV();
      PEV p = pEV.get(0);
      powerOutput = powerOutputs.getInt();
      get_Main().chargingCapacities.add(powerOutput);
   }
}
hasREG = bernoulli(get_Main().regOwners) == 1;
```

On every time step the following code is executed to get the energy pattern for that time step:

```
EnergyPattern eP = get_Main().getEnergyPattern(time(), this);
this.estimatedEnergy = eP.Estimated;
this.consumedEnergy = eP.Consumed;
if(this.hasREG) this.generatedEnergy = eP.Generated;

pevConsumption = pEV.sumConsumption();
```

It uses the `getEnergyPattern(Double time, Household household` method of the main agent.

A.4. Main agent

If houses are removed or added from the base number of households, 107, they are changed using the following code on model start up:

```
if(households.size() > 0){
   while(households.size() != numberOfHouseholds){
      if(numberOfHouseholds < 107) remove_households(households.get(households.size() - 1));
      else if(numberOfHouseholds > 107){
         Household h = households.get((int)uniform(0,106));
         add_households(h.id, h.selectedEnergyProfile, h.solarPanelCapacity,
             h.yearlyEstimatedConsumption, false, false, false, 0);
      }
   }
}
```

On model start-up, if a blockchain experiment is run, the following code is used to set-up a SSH connection. The connection is make through a PLink application instance, using a pre-defined PuTTY profile “CGI” for the first CGI virtual machine.

```
// only if blockchain experiment is running
if(Blockchain){
```

```
   try
   {
      // excetue plink from command line using preset CGI putty profile
      // store process in Main property "SSH"
      SSH = Runtime.getRuntime().exec("plink -load CGI");
      // collect all process streams into Main agent properties
      SSHOut = SSH.getOutputStream();
      SSHIn = SSH.getInputStream();
      SSHErr = SSH.getErrorStream();
   } catch(Exception e)
   {
      System.err.print(e);
   }
}
```

Below the function used to retrieve energy patterns per household per timeslot is given. It uses the Java API (Query DSL) to communicate with the database:

```
int mM = (int)modelMinutes;
double estimatedEnergy = (double) selectFrom(dbo_energy_patterns)
   .where(dbo_energy_patterns.home_id.eq(household.id),dbo_energy_patterns.model_minutes.eq(mM))
   .firstResult(dbo_energy_patterns.estimated);
int consumedEnergy = (int) selectFrom(dbo_energy_patterns)
   .where(dbo_energy_patterns.home_id.eq(household.id),dbo_energy_patterns.model_minutes.eq(mM))
   .firstResult(dbo_energy_patterns.consumed);
int generatedEnergy = 0;
if(household.hasREG){
   generatedEnergy = (int) selectFrom(dbo_energy_patterns)
      .where(dbo_energy_patterns.home_id.eq(household.id),dbo_energy_patterns.model_minutes.eq(mM))
      .firstResult(dbo_energy_patterns.generated);
}
return new EnergyPattern(estimatedEnergy, consumedEnergy, generatedEnergy);
```

A.5. PEV agent

The most important function of the PEV agent is its emergency charge fail-safe:

```
// If cars still leave the model with an SOC < 1.0
// the PEV's demand was to high to comply with considering
// the charger's output power

//remaining periods
int remP = (int)(sojournTime - (time() - arrivalTime)) / 15;

//required periods
int reqP = (int)Math.ceil((batteryCapacity - batteryLevel)/(powerInput / 4));

if(reqP >= remP-1){ // remP - 1 correctional period for simulation time discrepancies
   chargingPowerPeriod = powerInput / 4;
   return true;
}
return false;
```

B

Agent-based model validation

During model validation the correctness of the representation of the real system by the simulation model is tested [10]. Because of the high novelty of the modelled system, no data is available that could serve as a comparison to the model output data. Therefore, this appendix provides an statistical approach to the validation of the specified model. Based on the output of a parameter variation experiment in AnyLogic a multiple regression analysis will be used to prove causality between input parameters and the criteria. Hypotheses will be used to test the validity of the model behaviour against expectations in the real system.

B.1. Parameter variation experiment

In AnyLogic the parameter variation experiment is used to test how certain input parameters affect the model behaviour. The parameters were varied according to the expressions given in Table B.1. The inputs are randomly (uniform distribution) varied between upper and lower bounds. Penetration rates and fractions are varied to cover the full parameter range. The maximum number of 100 charging stations was chosen arbitrarily and the bounds for the number of households was based on expected coverage of the designed system, deducted from discussions with CGI experts on smart grids. To investigate transactional requirements, both smart and V2G charging is enabled.

Table B.1: Input parameter expression for parameter variation experiment

Number	Parameter	Expression
1	Car owning fraction	uniform(0, 1)
2	PEV owning fraction	uniform(0, 1)
3	REG owning fraction	uniform(0, 1)
4	BEV fraction	uniform(0, 1)
5	Public charging stations	(int) uniform(0, 100)
6	Average occupancy	uniform(0, 1)
7	Number of households	(int) uniform(50, 1000)

To test the validity of the simulation model's behaviour, the criteria were translated to output parameters, which are presented below. The mean as well as the confidence interval of these parameters are collected. The mean was chosen as dependent variable because it gives an insight in overall model behaviour. The resulting conclusions on causality can then be used to explore the extreme cases in simulation experiments. Below every output parameter, with desirable outcome, is explained sequentially.

Estimation deviation. During each run, per 15 minute interval, the absolute difference between estimated and actual, total consumption is collected and stored in a histogram. After each run the mean and confidence interval are stored as output parameters. The goal is to approximate the estimation deviation to zero.

SOC. The state of charge after each PEV's charging session, both household and public charging station, is collected into a histogram. After each run the mean and confidence interval are stored as output parameters. The goal is to approximate the SOC to one.

Charging cost. The CEMS database contained detailed information on electricity prices, dividing in supplier, network and tax costs. For each PEV charging session the total charging costs are collected in a histogram. After each run the mean and confidence interval are stored as output parameters. The goal is to keep the costs for charging as low as possible.

Charging earnings. The CEMS database contained detailed information on electricity prices, dividing in supplier, network and tax costs. For each PEV charging session the total discharging earnings are collected in a histogram. After each run the mean and confidence interval are stored as output parameters. The goal is to keep the earnings as high as possible.

Charging profit. The charging profit is the difference between the latter two parameters.

Transactional throughput. Energy trading between households and PEV result in transactions. For each 15 minute interval during a run the number of transactions is collected, resulting in throughput, and stored in a histogram. After each run the mean and confidence interval are stored as output parameters. The throughput is an important criterion for blockchain performance requirements.

Household transactions. After each simulation run the number of transactions per household agent is collected into a histogram. The mean and confidence interval are stored as output parameters. The goal is to keep the spread as small as possible, so that all household get an equal market share.

PEV transactions. After each lifetime of a PEV agent its number of transactions is collected into a histogram. After each run the mean and confidence interval are stored as output parameters. The goal is to keep the spread as small as possible, so that all PEVs have an equal burden of the balancing load.

B.2. Multiple regression analysis

The level of measurement of each input and output variable is on a ratio scale, as a result the generated data lends itself for a multiple regression analysis. Regression analysis focusses on explaining the relation between predictor variables and population parameters. Because of the interest in causal relations, standardised regression analysis was performed. By standardising, deviation in the output (dependent) parameter can be explained with variation in input (predictor) parameters. During the analysis, each dependent parameter was independently reflected against all predictors. Insignificant predictors are left out, resulting in a standardised regression model of the form

$$\hat{Y} = \beta_1 * z_1 + \beta_2 * z_2 + ... + \beta_n * z_n + \varepsilon, \tag{B.1}$$

where $\hat{Y}$ is the predicted output parameter, $\beta_1, ..., \beta_n$ are the partial standardised regression coefficients, $z_1, ..., z_n$ are the standardised predictor variables and ε is the standard error. Standardised coefficients mean that if the standard deviation of the predicted variable $\sigma_{\hat{Y}}$ increases with 1, the standard deviation of predictor i σ_{z_i} will have increased with β_i (within a 95% confidence interval). SPSS is used to fit the regression models.

For each output parameter, each input parameter's influence is tested using statistical hypothesis testing. This entails setting an expected outcome and checking if, with statistical relevance, the null hypothesis can be rejected. For variable z_i the null hypothesis is:

$$H0 : \beta_i = 0.$$

The confidence interval is set to 95%, resulting in an α of 0.05. Because expectations are tested, one-tailed significance is used, thus the p value should be smaller than 0.025. Subsequently, a description of the expected sign of each estimator per output parameter is given, of which a summary can be found in Table B.2. If the actual parameters match the expectations, model validity is justifiable (within a 95% confidence interval).

Deviance. PEVs are assumed to increase deviation between estimated and actual consumption, because the demand peaks outweigh the balancing effects. Therefore, the car owning fraction (z_1) and PEV penetration rate (z_2), as well as the number of public charging stations (z_5) and average occupancy (z_6), are expected to have positive causal relations with the estimation deviation. REG (z_3) is hard to predict by BRPs and therefore, by definition, increases the deviation from consumption estimation. Most BEVs have a higher battery capacity than PHEVs, because the effects of charging are assumed to outweigh the balancing capacity, a larger share of BEVs (z_4) will increase the average deviation. Deviations occur because individual households do not match the generalisations on which the electricity profiles are based. If the number of households (z_7) increases, the mismatches will grow accordingly and with it the average deviance.

SOC. A higher percentage of car owners (z_1) and/or a higher fraction of PEV owners (z_2) will result in a larger buffer capacity owing to a larger battery fleet. Therefore, the amount of electricity discharged per vehicle in case of underestimation is lower and the average SOC increases. The penetration of REG (z_3) is expected to have a positive causal relation with SOC, because more generation will lead to more surplus and thus more charging chances. Due to the, on average, higher battery capacity of BEVs compared to PHEVs, the chance of leaving with a partially charged battery becomes larger. As a result, the average SOC goes down with higher shares of BEV (z_4). Because PEVs at public charging stations have shorter sojourn times than those connected at households, the chance of over-demand is expected to outweigh the positive effects of a larger available battery buffer. Conclusively, the mean SOC will drop when the number of charging stations (z_5) is increased. The occupancy (z_6) of public charging stations is expected to increase the number of publicly charging PEVs, thus will also lower the average SOC. The number of households (z_7) is expected to have a positive causal relation with the average SOC, because more household will result in more periods of overestimation and thus more opportunities for smart charging.

Charging cost. It is inherent to the CEMS database that moments of overestimation occur at times of high market prices. Consequently, due to smart charging, charging occurs during these times of high prices. However, with an increase in the number of available PEVs (z_2) (increased indirectly through the car owning fraction (z_1), these high costs can be shared amongst more PEV owners. As the emergency charging will occur later, most likely during lower prices, the average charging sessions costs go down. The amount of available REG (z_3) is assumed to have an decreasing effect on charging costs, due to the coinciding times of generation and low market prices. Due to the, on average, higher battery capacity of BEVs compared to PHEVs, the costs to fully charge a battery are assumed to grow with growing BEV share (z_4). Increased numbers of charging stations (z_5) and higher occupancy (z_6) will have a similar effect on charging costs as the number of household PEVs. An increase in the number of households (z_7) will lead to an increase in charging costs as the deviations during overestimation will increase, requiring more smart charging during times of high market prices.

Charging earnings are inversely linked to the costs. With more cars (z_1) and a higher PEV penetration (z_2), earnings have to be shared amongst more, thus will decrease. The same holds for the number (z_5) and occupancy (z_6) of public charging stations. Larger battery capacities, a result of a higher BEV fraction (z_4), allow for larger sales of electricity and will hence increase earnings. With an increase in the number of households (z_7) comes an increase opportunity for trading energy during periods of underestimation. The amount of REG (z_3) is assumed to have an increasing effect on earnings, as the PEVs will charge during periods where electricity is cheap, and possibly selling this at a later, higher priced, time.

Profit is calculated by subtracting earnings from cost. The sing of these parameters is essentially an indication on which parameter has the largest influence.

Throughput. Transactions occur whenever there is excess or a shortage of electricity and available battery capacity. Therefore, the penetration of cars (z_1) and PEVs (z_2), as well as the number of public charging stations (z_5) and their average occupancy (z_6), and the number of households (z_7) will have a positive causal relation with transactional throughput. The same holds for the penetration rate of REG (z_3). Because the BEV fraction (z_4) is expected to increase the average battery capacity, and thus allows for imbalance mitigation with fewer cars , the number of required transactions decreases.

Household transactions. An increase in the fraction of car owners (z_1) will lead to more PEVs through the PEV penetration rate (z_2). The same holds for the number of public charging stations (z_5) and average occupancy of aforementioned stations (z_6). If there are more PEVs, more of the mismatch between household consumption and estimation patterns can be covered by trading electricity. Vice versa, the number of households (z_7) is expected to have a negative relation with the number of household transactions, as at some point the maximum capacity is reached. A higher average battery capacity, indirectly caused by the BEV fraction (z_4), will increase the available balancing buffer, increasing the number of household transactions. Finally, the penetration of REG (z_3) will increase the amount of household transactions, due to the increased surplus of household energy, which is an ideal source for PEV charging.

PEV transactions. For the number of PEVs, through predictors (z_1, z_2, z_5) and (z_6), and the number of households (z_7) are expected to have an opposite effect on the number of PEV transactions compared to the number of household transactions. The effect of the penetration of REG (z_3) and the BEV fraction (z_4) will have similar effects on the number of PEV transactions as on the household transactions.

Table B.2: Alternative hypotheses per predictor per output parameter

$\hat{Y}$	$H1:\beta_1$	$H1:\beta_2$	$H1:\beta_3$	$H1:\beta_4$	$H1:\beta_5$	$H1:\beta_6$	$H1:\beta_7$
Deviance	>0	>0	>0	>0	>0	>0	>0
SOC	>0	>0	>0	<0	<0	<0	>0
Cost	<0	<0	<0	>0	<0	<0	>0
Earnings	<0	<0	>0	>0	<0	<0	>0
Profit	?	?	?	?	?	?	?
Throughput	>0	>0	>0	<0	>0	>0	>0
Household txns	>0	>0	>0	>0	>0	>0	<0
PEV txns	<0	<0	>0	>0	<0	<0	>0

B.2.1. 1st iteration regression analysis results

The parameter variation experiment consisted of 276 runs. Table B.3 gives the results of the regression analysis. Parameter values β_i give an insight in the direction of causal relation and how strong its influence is. The R^2 statistic gives the degree to which the output parameter's variation can be explained by the regression model. If a parameter value is zero, the predictor had an insignificant contribution to output variability, and therefore it is assumable that no causal relation exists.

Table B.3: 1st iteration regression analysis results

$\hat{Y}$	β_1	β_2	β_3	β_4	β_5	β_6	β_7	R^2
Deviance	0.491	0.456	0	0	0.132	0	0.518	0.759
SOC	0.304	0.321	0	-0.201	-0.280	0	0.240	0.409
Cost	-0.558	-0.518	0	0.182	-0.143	-0.110	0.166	0.643
Earnings	-0.381	-0.347	0	0	-0.329	-0.147	0.274	0.460
Profit	0.148	0.126	-0.040	0.113	0.386	0.133	-0.292	0.325
Throughput	0.019	0.021	-0.112	0.034	0.045	0.045	0.994	0.982
Household txns	0	0.099	-0.605	0.196	0.248	0.232	0	0.597
PEV txns	-0.041	-0.009	-0.066	0.041	-0.464	-0.290	0.471	0.563

When analysing the results the first remarkable conclusion that can be drawn, is the seeming absence of the effects of the penetration of REG. For half of the output parameters the predictor had no significant impact. For the others outputs the causal relation's polarity does not match the expected polarity. Therefore, the model structure was re-scrutinised and two critical flaws concerning REG were discovered and fixed:

- The amount of generated energy was not taken into account in the pattern plots, nor the estimation deviance histograms. When there is a sufficient generation the grid has the potential to become net suppliers. The moments and amounts of energy generated are hard to predict by BRPs and as such the penetration of REG will have a profound influence of the aforementioned plot and histogram. The error was corrected by adding surplus (total generation minus household consumption) to both statistics.

- In case there was a net supply of electricity coming from REG, no trading between household and PEVs occurred, while this an eminent moment for PEv charging. The problem was fixed by enabling trade in the case of generation surplus.

In order to investigate the validity of the new model, the parameter variation experiment and multiple regression analysis were revisited.

B.2.2. 2nd iteration regression analysis results

The second iteration of the regression analysis, after fixing the model errors discovered during the first analysis, was based on a parameter variation experiment with 911 runs. The partial regression coefficients can be found in Table B.4.

Table B.4: 2nd iteration regression analysis results

$\hat{Y}$	$H1:\beta_1$	$H1:\beta_2$	$H1:\beta_3$	$H1:\beta_4$	$H1:\beta_5$	$H1:\beta_6$	$H1:\beta_7$	R^2
Deviance	0.443	0.443	0.080	0[a]	0.073	0.077	0.582	0.778
SOC	0.349	0.327	0[a]	-0.215	-0.294	-0.163	0.230	0.399
Cost	-0.490	-0.558	0[a]	0.193	-0.082	-0.114	0.113	0.581
Earnings	-0.324	-0.383	0[a]	0[a]	-0.275	-0.241	0.286	0.451
Profit	0.109	0.147	0	0.115	0.359	0.279	-0.348	0.356
Throughput	0.03	0.033	-0.116[a]	0.029[a]	0.043	0.051	0.974	0.975
Household txns	0.134	0.146	-0.558[a]	0.118	0.230	0.250	-0.087	0.493
PEV txns	0[a]	0[a]	-0.118[a]	0.065	-0.417	-0.324	0.492	0.520

[a] Mismatch between alternative hypothesis and coefficient (polarity).

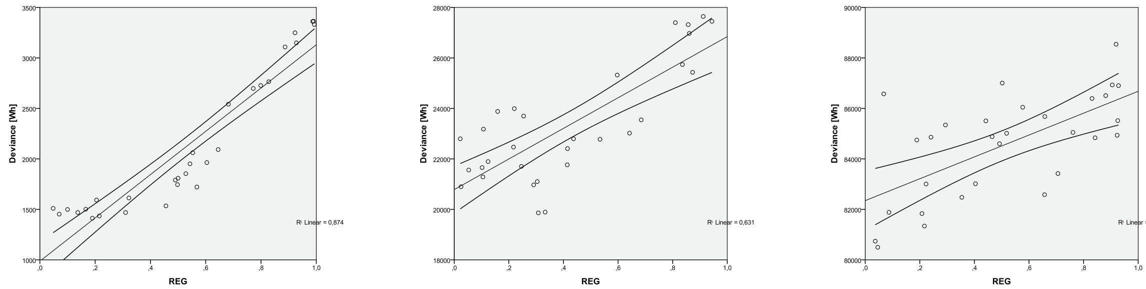
Sensitivity analysis of the penetration of REG

After the second iteration the partial regression coefficients have not changed significantly for the penetration of REG predictor. Thus, the models behaviour as a result of REG penetration is further explored by conducting a sensitivity analysis on the penetration of REG. The predictors that affect the number of PEVs and households seem to have an overall strong influence. Therefore, the sensitivity of the penetration of REG is tested in three scenarios with increasing penetrations of PEVs and number of households. The sensitivity is tested against the deviance mean, because the amount of generated energy is assumed to have the largest effect on this parameter. The experimental design is summarised in Table B.5. The analysis will generate a scatter plot for each experiment. The expectation is that the amount of REG has a positive causal relation with deviation. The scatter plots should therefore show a more profound positive linear relation than is evident from the parameter variation experiment. The outcomes are graphically presented in Figure B.1.

Table B.5: REG penetration sensitivity analysis experiment design

Experiment	REG	PEV	BEV fraction	Charging stations	Households
1	uniform(0, 1)	0.01	0.01	1	100
2	uniform(0, 1)	0.50	0.50	50	500
3	uniform(0, 1)	1.00	1.00	100	1000

As can be seen from the figures in Figure B.1 there is an strong relation between the penetration of REG and the estimation deviance for growing numbers of PEV and households. The R^2 of the fitted lines is significant throughout the three scenarios (the curved lines represent the 95% confidence interval). This means that the amount of REG can explain some of the variability in the deviance. However, as the number of PEVs and households increases this effect diminishes, concluding from the reduction in R^2. This in combination with the results from second regression analysis, leads to the conclusion that overall the model structure can be deemed adequate and that it's highly probable that the amount of PEVs and households has a bigger impact on the output parameters than the penetration of REG.

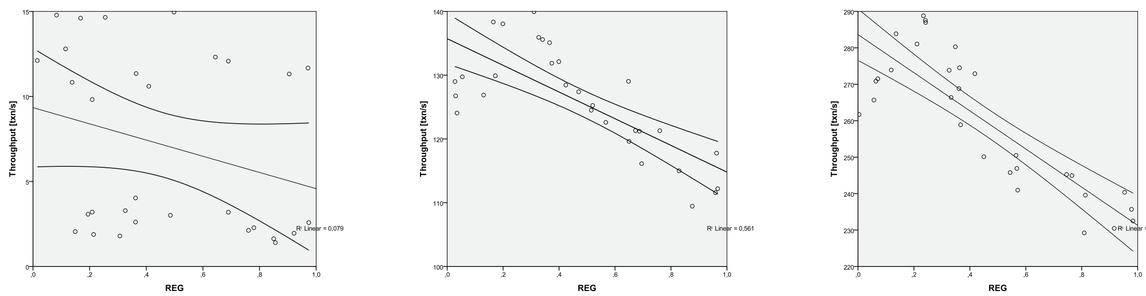


(a) Experiment 1 (b) Experiment 2 (c) Experiment 3

Figure B.1: Scatter plots for the REG penetration sensitivity analysis on the estimation deviance

The effect of the penetration of REG appears to have a strong inverse relation with the number of transactions occurring, compared to what was expected. The amount of generated electricity can only contribute to the number of transactions when there is surplus, i.e. the sum of household generation exceeds the sum of household consumption. In scenarios with low REG penetration there is no chance of having surplus and thus there is no effect of changes in REG. When there is a higher amount of REG transactions can occur if and only if there are plugged-in PEVs during moments of surplus. At lower penetration of PEVs and number of households, this chance is small. This is visible in Figure B.2a, where dots are scattered at random and the fitted negative zero order polynomial has a very low R^2 statistic. The R^2 statistic increases through Figure B.2b and B.2c, signalling an increasingly strong causal relation at larger PEV penetration and number of households.

The partial regression coefficients for the output parameters relating to energy transactions (substantially) differ from the alternative hypotheses presented in Table B.2. While, deducing from the model structure, one would expect an increase in transactional throughput, the relation between indicator and output parameters (see also Figure B.2).



(a) Experiment 1 (b) Experiment 2 (c) Experiment 3

Figure B.2: Scatter plots for the REG penetration sensitivity analysis on throughput

After the sensitivity analysis on the relation between the REG fraction and throughput, the model's specification was revisited. It was found that there was a misplaced piece of code in the trading algorithm, that prevented the discharging of PEVs during times of high REG. The error propagated through the model by being doubly accounted for in model statistics and figures. The algorithm's structure was changed so that it correctly accounts for high generation from solar panels. A third sensitivity analysis was conducted to support this claim (see figure B.3). The figure shows that the number of transactions per time unit increases, as it to be expected.

B.2.3. 3rd iteration regression analysis results

The third iteration of the regression analysis, after fixing the model errors discovered during the second analysis, was based on a parameter variation experiment with 210 runs. The partial regression coefficients can be found in Table B.6. It is evident that the influence of the REG penetration is still questionable. Considering the dependence on the number of households, i.e. you need households for REG, and the results of the sensitivity analysis (see Figure B.3), the model's validity is not rejected based on the partial regression coefficients.

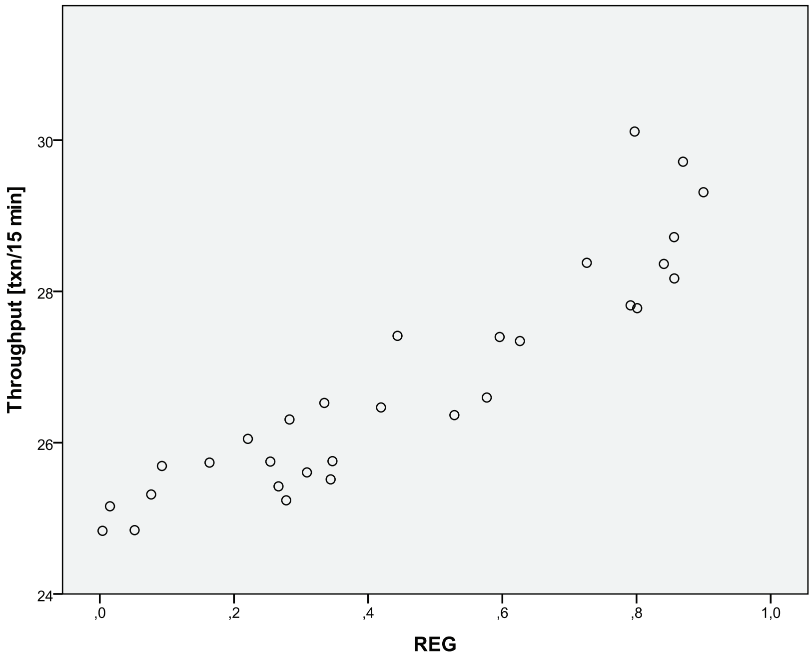


Figure B.3: Scatter plot for the second REG penetration sensitivity analysis on throughput

A similar explanation is considered for the lack of influence of the BEV fraction indicator. The BEV fraction only has an indirect influence on criteria through PEV penetration and the car owning fraction. The effects of these factors is deemed to outweigh the effects of the BEV fraction, resulting in insignificant partial regression coefficients.

Actually, if one compares the parameters from the second iteration (Table B.4) with that of the last iteration (Table B.6), the only mismatches between alternative hypothesis and coefficient polarity occur at insignificant coefficients. The differences between the coefficients of both analyses are small, leading to conclude that the model displays some robustness.

Table B.6: 3[nd] iteration regression analysis results

$\hat{Y}$	$H1:\beta_1$	$H1:\beta_2$	$H1:\beta_3$	$H1:\beta_4$	$H1:\beta_5$	$H1:\beta_6$	$H1:\beta_7$	R^2
Deviance	0.443	0.417	0[a]	0[a]	0.104	0.085	**0.560**	0.734
SOC	0.243	0.283	0[a]	-0.249	-0.293	-0.137	**0.328**	0.397
Cost	**-0.497**	-0.460	0[a]	0.243	-0.164	-0.166	0[a]	0.541
Earnings	**-0.332**	-0.310	0[a]	0[a]	-0.312	-0.239	0.240	0.391
Throughput	0.163	0.132	0[a]	0[a]	0.142	0.148	**0.906**	0.924
Household txns	0.396	0.289	0.086	0[a]	0.362	0.336	**-0.464**	0.690
PEV txns	-0.362	-0.308	0[a]	0[a]	**-0.384**	-0.301	0.300	0.533

[a] Mismatch between alternative hypothesis and coefficient (polarity).

B.3. Parameter variation analysis conclusions

From Table B.6 it can be concluded that there are mismatches between the alternative hypotheses and their partial regression coefficients of some of the predictors.

Where the coefficients are zero, their effects were insignificant compared to the other indicators. Such is the case for the amount of PEVs (z_1 and z_2) on the number of PEV txns. A likely explanation is that the effect of randomly appearing PEVs at public charging stations have a more profound effect. This is supported by β_5 and β_6. Maintaining the null hypotheses for the coefficients of the BEV fraction for deviance and earnings, could be explained by the fact that the input only has an indirect influence on the average battery capacity.

Therefore, the number of PEVs has a much stronger effect, which is shown by β_1 and β_2 for both output parameters.

For all the output parameters the level of variance that can be explained by the regression model, based on the R^2 statistics, is relatively high. $R^2 > 0.300$ is often deemed a sufficient level in social sciences and all statistics lie above that with a sufficient margin. Out of all predictors the number of households seems to have the largest influence on the output parameters, having the maximum absolute coefficient for the deviance, throughput and PEV transactions. On all these outputs the number of households seems to have an undesirable effect, namely one would want the deviance to be low and the number of transactions low. The number of households is expected to be an important indicator for blockchain performance limits and will be thoroughly tested during the experimental/simulation phase.

The number of household PEVs, effected through z_1 and z_2, is another critical indicator, having the strongest causal relation with mean SOC, cost and earnings. While increasing the number of PEVs has a preferable effect on SOC, and costs also seem to decrease, the earnings decrease. The net result of cost and earnings also seems to benefit. However, these conclusions apply for the mean values and say nothing about extremities. Therefore the maximum costs and minimum earnings under increasing penetration of PEVs will be an important topic during the experimental phase. The largest disadvantageous predictors on the SOC β_4 and β_5, the fraction of full-electric PEVs, respectively the number of public charging stations. It is expected that these coefficients are smaller because their effects are only indirect, namely through the average battery capacity and charger output power. During the experimental phase these indicators will be analysed directly for their effects on SOC.

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