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Simulating smart charging in Dutch neighbourhoods

Developing an agent-based model to analyse the interaction between spot markets and smart charging

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Master thesis Energy Science

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Executive summary

The electrification of transport increases the peak electricity demand in the electricity network at times people arrive at work or come home from work. At the same time, the electricity produced by intermittent renewables is increasing as well. Their intermittency also causes high load peaks on electricity networks and make it hard to match electricity supply and demand. These trends make smart charging based on price optimisation an increasingly interesting solution to reduce electricity costs for EV charging and match supply and demand on spot markets.

At the TU Eindhoven an agent-based model is developed to answer questions about the future Dutch EV environment. The model is called the agent-based model for the buying, charging and driving of electric vehicles (the ABCD model) (Auke Hoekstra 2017). The purpose of the ABCD model is to simulate the EV environment of a specific neighbourhood, so different stakeholders can understand the needs of future charging infrastructures. Smart charging will also be part of this future charging infrastructure. It would be interesting for stakeholders to be able to analyse smart charging in Dutch neighbourhoods. Therefore, the following research goal is formulated for this research.

Develop a module for the ABCD model to simulate smart charging based on price optimisation in a neighbourhood.

The smart charging module will enable stakeholder to assess the following questions:
Electricity supplier: How much charging load in the neighbourhood is flexible due to smart charging? **Local grid operator:** When do load peaks occur and how high are these load peaks in the neighbourhood when smart charging is applied? **EV owner:** With what percentage are the charging costs reduced when smart charging is applied? **Dutch government:** What is the percentage increase in charged renewables when smart charging is applied? **Energy investor:** What is the percentage increase in revenue for renewable generated electricity sold on the day-ahead spot market when smart charging is applied?

The smart charging module is simulating spot market prices and using those prices to optimise the charging sessions in the simulations of the ABCD model. Also, the charging load of the EVs is translated to an increase in demand on the spot market to assess the interaction between charging and spot markets.

The spot market price simulation is validated with 2016 prices. The smart charging simulations are validated by relating the outputs to the input parameters in different scenarios. The scenarios are also used as example scenarios that can be assessed with the ABCD model including smart charging.

Some striking conclusions are drawn with the scenario analyses. Firstly, smart charging is shifting 90% of the charging load from the early morning and late afternoon to midnight. This indicates the great potential to use smart charging for balancing electricity portfolios of energy suppliers. Secondly, charging costs can be reduced with around 32% which is equal to 5 €/month per EV in 2025. Thirdly, smart charging can increase renewable generated electricity with 18% in 2025. And lastly, revenues for renewable generators are decreasing when smart charging is applied due to a decrease in average spot market prices.

Keywords: Smart charging, Smart energy systems, Electric vehicles, Spot market, Renewable generation, Agent-based modelling, Cost-effective electricity network

Statement of originality

Herewith I, Michiel van Lelyveld, declare that I have written the following master thesis myself and have not used other sources and media than posted / listed in the work and made all direct and indirect thoughts that were used from external sources recognizable as such.

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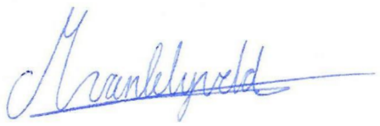

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Yours sincerely,

Michiel van Lelyveld

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1 Introduction

1.1 The synergy between intermittent renewables and smart charging

The share of electric vehicles (EV's) is increasing in The Netherlands (RVO 2017), due to decreasing cost of battery packs and policy incentives(Maarten Cuijpers, Auke Hoekstra, and Wouter Bakker 2016). Over the coming decades, the cost of battery packs are likely to decrease further (Bloomberg Finance, 2017; Goldman Sachs, 2016; Nykvist & Nilsson, 2015) to a point where energy and maintenance cost savings of electric vehicles will outweigh battery costs (Bloomberg Finance 2017; Maarten Cuijpers, Auke Hoekstra, and Wouter Bakker 2016), resulting in quickly increasing electric vehicle sales (International Energy Agency 2016; Bloomberg Finance 2017).

The electrification of transport increases the peak electricity demand in the electricity network at times people arrive at work or come home from work. At the same time, the electricity produced by intermittent renewables is increasing as well. Their intermittency also causes high load peaks on electricity networks and make it hard to match electricity supply and demand. Research has found that this mismatch between supply and demand on electricity spot markets results in higher price volatilities (Green & Vasilakos, 2009; Sensfuß et al., 2008). Higher volatility makes smart charging based on price optimisation an increasingly interesting solution to reduce electricity costs for EV charging.

The mismatch between supply and demand on spot markets also reduces the revenue per kWh of renewable generated electricity. The revenue decreases because high penetration of renewable energy decreases spot market prices (Ueckerdt, Hirth, Luderer, & Edenhofer, 2013). This phenomena is researched extensively and is called the profile effect (Agora Energiewende, 2013; Brouwer, Van Den Broek, Seebregts, & Faaij, 2014; Sijm, 2014).

The powerful synergy of intermittent renewables and smart charging is that spot market demand is increased at times of high penetration of renewable energy. This decreases the profile effect, thus increasing the revenues for renewable generation. Thus, with increasing intermittent renewables, smart charging becomes an increasingly interesting solution to create a cost effective electricity system.

1.2 Agent-based model to analyse the future Dutch EV environment

At the TU Eindhoven an agent-based model is developed to answer questions about the future Dutch EV environment (Auke Hoekstra 2017; Vijayashankar 2017; Dai 2017). The model is called the agent-based model for the buying, charging and driving of electric vehicles (the ABCD model) (Auke Hoekstra 2017). The purpose of the ABCD model is to simulate the EV environment of a specific neighbourhood, so policy makers can understand the needs of future charging infrastructures. Agent-based modelling (ABM) is eminently useful to simulate unknown dynamics of a system, if the behaviour of individual components is well defined.

Research has been done about the use of ABM for the analyses of the future Dutch EV environment (Bruch & Atwell, 2015; Eidelson, 1997; Holland, 2006). ABM is used in the ABCD model to simulate realistic behaviour inside a Dutch neighbourhood that the user wants to analyse. The road network, electricity network and houses of the neighbourhood can be uploaded with GIS data. The ABCD model simulates the behaviour of the residents in this neighbourhood. A resident agent can buy and drive his EV and charge the EV at a charge point in the neighbourhood. A flowchart and summary of the ABCD model can be found in Appendix 8.1.

1.3 Problem definition and research goal

The ABCD model is a tool to analyse future scenarios concerning the future EV charging infrastructure. Smart charging will also be part of this future charging infrastructure. However, smart charging cannot be simulated with the ABCD model. Smart charging would be a valuable addition to the ABCD model. Therefore, the following research goal is formulated for this research.

Develop a module for the ABCD model to simulate smart charging based on price optimisation in a neighbourhood.

Examples of questions from stakeholder that can be answered with the module are:
Electricity supplier: How much charging load in the neighbourhood is flexible due to smart charging? **Local grid operator:** When do load peaks occur and how high are these load peaks in the neighbourhood when smart charging is applied? **EV owner:** With what percentage are the charging costs reduced when smart charging is applied? **Dutch government:** What is the percentage increase in charged renewables when smart charging is applied? **Energy investor:** What is the percentage increase in revenue for renewable generated electricity sold on the day-ahead spot market when smart charging is applied?

1.4 Research framework

The smart charging module is connected to the ABCD model via the charge points as is indicated by **Error! Reference source not found.**. The smart charging module is divided into three boxes:

BOX 1: Simulating spot market prices to enable smart charging based on price optimisation.

BOX 2: Makes optimised charge schedules for the charge points in the ABCD model neighbourhood using the spot market prices of BOX 1.

BOX 3: Translating the charging load in the simulation to an increase in demand on the spot market.

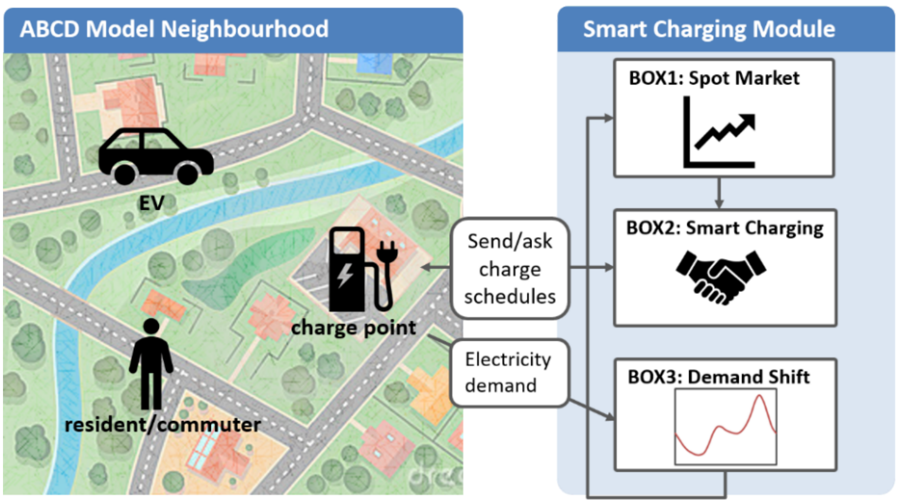


Fig. 1 Flowchart of the smart charging module. The module is divided into three boxes. The module is interacting with the ABCD model via the charge points in the neighbourhood.

These three elements define the research framework. Throughout this report, this framework is used to divide the chapters into three sections. The smart charging module is divided into three boxes that represent these mechanisms as shown in **Error! Reference source not found.**. **Error! Reference source not found.** shows the ABCD model with the smart charging model incorporated.

The smart charging is regulated by a virtual entity called the aggregator. As was mentioned in the previous paragraph, the smart charging module is used to control the charge points in the ABCD model neighbourhood simulation. The development of the boxes is based on the assessment of the following sub questions:

BOX 1: How to simulate electricity prices on day-ahead spot markets?

BOX 2: How will commercial parties apply smart charging based on price optimisation in The Netherlands?

BOX 3: How can the increase in spot market demand due to charging be estimated?

1.5 Chapter outline

This report is a model development paper and the chapters are structured accordingly. Chapter 2 "modelling approach" is a theoretical foundation for the development of the model. The sub-questions are discussed in this chapter with a short methodology and the conclusions per sub-question. Chapter 3 "model development" gives an outline of the module boxes with the crucial assumptions that were made to develop the boxes. Chapter 4 "model validation" presents a method to validate the model and presents the results of this validation. The module boxes are validated separately by relating the box outputs to the box inputs under different input scenarios.

BOX 3 is validated with a scenario analyses using the complete ABCD model with smart charging module. This allows to validate the whole model and to give an example of scenarios that can be tested with the new smart charging module. Four scenarios are tested:

1. Low renewable generation and low EV adoption.
2. High renewable generation and low EV adoption.
3. Low renewable generation and high EV adoption.
4. High renewable generation and high EV adoption.

This scenario analysis is also used to reflect back on the first section in this introduction, where the complementary characteristic of renewable generation and EV adoption is discussed.

1.6 Research focus and boundaries

This research puts focus on the interaction between the prices on a day-ahead spot market and smart charging. For this reason, the sub questions focus on the pricing method on day-ahead spot markets, the process of smart charging based on price optimisation and the translation of charging demand on the demand on spot markets.

This research does not focus on the prediction of future electricity prices or EV deployment. Predictions on fuel prices, CO_2 prices, renewable electricity supply and conventional supply are included in the smart charging module, but are not claimed to be strongly founded. Predictions about the behaviour of EV owners concerning charging is used from the ABCD model. Trends in weather patterns, other storage and demand response technologies and fuel cell electric vehicles (FCEV) are outside the scope of this research. These trends are influencing the future prices on spot markets, but are considered irrelevant for the relation between smart charging and a spot markets.

1.7 Scientific and social contribution

Matching demand and supply in electricity grids of electricity based economies, is currently one of the mayor topics in the field of energy science. With growing renewable penetration and EV's in The Netherlands, smart charging might become an important technique to match demand and supply in the future energy system. By doing so, smart charging has the potential to play an important role in reducing CO_2 emissions. The ABCD model with the smart charging module enables a new method to analyse the up and downsides of smart charging based on price optimisation.

For the first time a model is developed that includes the agent-based EV dynamics of neighbourhoods but also includes global effects as electricity prices, battery prices and policy effects. As the set-up for the ABCD model is agent-based, it is easy to adopt the model to new changes in the Dutch EV environment. This is very important in the performance assessment of technologies like smart charging that are so sensitive to small changes in price volatilities, charging infrastructure and EV usage.

Also, simulating smart charging in an agent-based simulation of a neighbourhood will allow to determine unforeseen effects of smart charging on neighbourhood level. This supports the discussion between policy makers and grid operators on how the future low and medium voltage networks should be maintained and developed.

The social contribution of the ABCD model lies in its application. The model can be used by Dutch policy makers to understand the needs of future charging infrastructures. By understanding these needs, better decisions can be made in creating regulation and making investments.

Finally, the analyses of smart charging in terms of costs and impact on LV networks supports grid operators and commercial parties in designing a cost effective electricity system. Grid operators can for instance compare the cost benefits of smart charging with the costs of new electricity cables. Commercial parties in the energy sector can simulate smart charging in future scenarios to analyse the cost benefits of smart charging.

End of chapter 1: Introduction

2 Modelling approach

2.1 Pricing on electricity spot markets

This section elaborates on the first sub question: How to simulate electricity prices on day-ahead spot markets? To answer this question, literature research has been done about the economics of day-ahead spot markets. This section summarises the relevant findings of this literature study.

Two sided auction model

The mechanism that is used for pricing on the Dutch spot market (EPEX NL day-ahead, former APX) is based on the two-side auction model (Drs.ir. M.P.G. Sewalt, 2003; EPEX SPOT, 2016; Roth, Alvin E.; Sotomayor, 1992). In a two-sided auction, the suppliers submit "blind" offers and the bidders submit "blind" bids when the auction is opened. In this context, blind means that the suppliers and bidders cannot see the actual offers and bids of other parties. When the market closes, demand and supply are compared in a so called merit-order for every hour on the day ahead. This type of price determination is based on the economic theory of supply and demand (Geman & Roncoroni, 2006). Fig. 2 shows an example of a merit-order with supply and demand curve and their intersection.

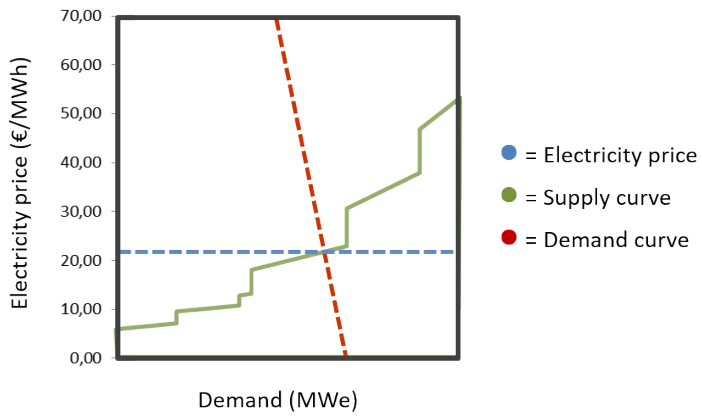


Fig. 2 Merit-order with supply curve, demand curve and their intersection. In the economic theory of supply and demand, the intersection of the curves indicates the market price in a two-sided auction model. The constitution of the merit-order for determining a spot market price, is referred to as merit-order matching.

Supply curve based on installed conventional generation capacity and SRMC

The supply curve is typically shaped by the short run marginal costs (SRMC) of the generators that produce the suppliers electricity, as indicated by the different levels in the supply curve of Fig. 2. The reason for this is that suppliers offer electricity at the lowest price at which they can sell with profit. This price is equal to the variable production cost of electricity per unit of time, called the SRMC.

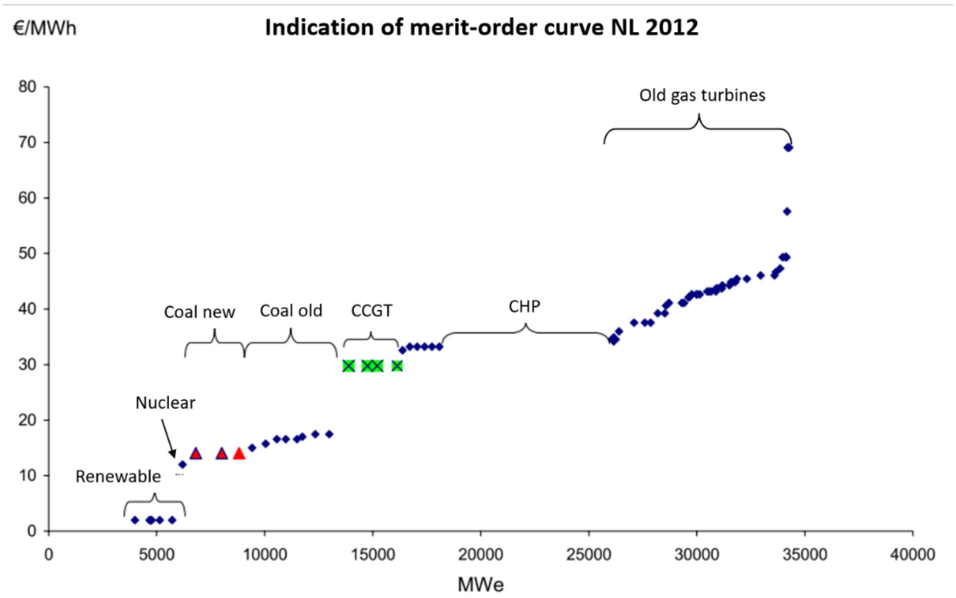
The SRMC of a specific generator is quite stable and depending on fuel costs, operation and maintenance costs, carbon tax costs and sometimes insurance costs. The equation for the SRMC is given by equation (1).

$$SRMC = \frac{Variable\ costs}{Electricity\ produced} = F + CO_2 + O\&M \tag{1}$$

With SRMC in €/MWh, F the fuel costs in €/MWh, CO_2 the emission costs in €/MWh, and O&M the operation and maintenance costs in €/MWh. For conventional generators like coal and gas plants, this formula is widely accepted.

Apart from the SRMC of the generators the supply curve is determined by the generation capacity that is available at a specific moment. In

Fig. 3 a supply curve is visualised where the X-axis represents the generation capacity and the Y-axis the SRMC. This supply curve for the Dutch spot market has been constructed by the research institute ECN



(Ybema et al., 2012).

Fig. 3 Indicative merit-order curve for The Netherlands in 2012 made by ECN (Ybema et al., 2012). The SRMC's of the generators determine the height of the points and the generation capacity the horizontal distance between the points. The type of generator is indicated in the graph. The new coal generators are market with red triangles and the new CCGT's are market with green squares.

Supply curve based on the relation between demand and spot market prices

During this research a second method for constructing the supply curve is developed and tested. This method is based on the correlation between spot market prices and the hourly average electricity demand. These two variables show a strong correlation which can be expressed with a function that can serve as supply curve. In the remaining part of this report, this supply curve will be referred to as the fitted supply curve.

In Fig. 4 the APX day-ahead prices of 2016 are plotted against the average hourly load of 2016 in The Netherlands. Firstly, the hourly load is adjusted to make the data independent of renewable generation. The relation between prices and demand needs to be independent from renewables to create a supply curve for conventional generators. By subtracting the renewable generation from the total load, the correlation between conventional supply and APX prices becomes visible. This relation observed in the data is used to fit a supply curve that relates the conventional supply to the electricity prices.

A linear trend can be observed in Fig. 4 between an electrical load of 5000 MWe and 15000 MWe. A linear trend line is fitted over this range of prices indicated by the dotted line and *equation y1* in the figure. This range of loads corresponds to generation by the conventional generators: nuclear, new coal, CCGT and CHP plants. With higher loads, the slope of the relation grows increasingly. In this region the relation between prices and demand becomes similar to an exponential function. This load region corresponds to older gas generators that only run when demand is exceeding the expected load. To account for this relation an exponential component is added to the linear trend y1. The resulting function is indicated by the black line and *equation y2*.

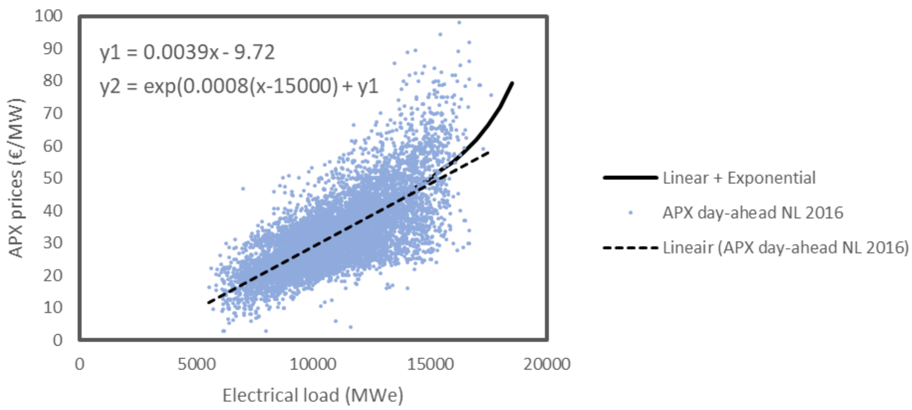


Fig. 4 Supply curve fitted on 2016 APX prices. The blue dots indicate the APX prices depending on the 2016 NL hourly demand (Entso-e, 2016; EPEX SPOT, 2016). The equations of the fitted curves are indicated by y1 and y2 in the figure.

2.2 Application of commercial smart charging

This section is dedicated to the second sub question: How will commercial parties apply smart charging based on price optimisation in The Netherlands? The method used to examine this question is to conduct interviews with experts in the field of e-mobility and demand response applications. The main conclusions of the interviews are also presented in this section.

Interviewing experts about smart charging based on price optimisation

Currently, there is no consensus about how smart charging will be applied by commercial parties. Pioneers in the e-mobility sector have the best understanding of the latest developments in smart charging and are therefore interviewed for this research. Although this approach does not ensure that the simulation of smart charging will be realistic, the interviews give ground to some of the decisions that are made for the development of the smart charging module.

Three experts from different organisations are interviewed about their vision on the implementation of smart charging in the Dutch charging infrastructure. These experts are:

1. Stan Janssen from ElaadNL, smart charging software expert
2. Auke Hoekstra from ElaadNL, Alliander and TU/e, e-mobility expert (Hoekstra, 2017)
3. Derek de Rie from Senfal, demand response software expert (De Rie, 2017)

Stan Janssen is an in-house programmer at ElaadNL. One of his roles inside the organisation is to research the opportunities for smart charging in The Netherlands and the software that could be used for this. Auke Hoekstra has been involved in the development of e-mobility in The Netherlands for over 20 years. As head of the ABCD project he is also giving his vision on the implementation of smart charging in The Netherlands. Derek de Rie has been designing commercial demand response software for Senfal and also has experience with smart charging.

Interview questions

To understand what the requirements are for a proper simulation of smart charging, there are three processes that need to be examined. These processes are the communication between the aggregator and EV owner, the process of buying electricity on the spot market by the aggregator and the process of charging the EV's. The following three questions focus on these processes and are used for the interviews:

1. How will the charging requirements of the EV owner be communicated to the aggregator?
2. How does the aggregator determine the amount of electricity that is needed for charging EVs the following day?
3. How will the aggregator determine optimal charging times using spot market prices?

Communication of charging requirements of EV owner to aggregator

The charging requirements of the EV owner need to be communicated at the moment the owner plugs in the EV into the charging station. The most probably channel of communication will be a smart phone application of the aggregator. This application should be able to communicate the amount of kWh that the user wants to charge and the timeframe in which this charge session can take place.

Currently, there is one commercial party in the Netherlands that applies smart charging based on price optimisation called Jedlix (Jedlix, 2017). They work with a smart phone application that enables the communication between them and the EV owner. At the moment the EV owner plugs in his EV the aggregator will know what the constraints are for using the EV battery for smart charging. Jedlix can decide when the battery will be charged and how fast this will happen, without violating the user constraints. The user interface of the application is shown in Fig. 5.

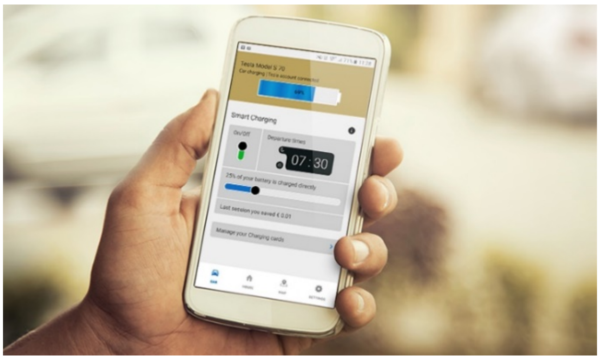


Fig. 5 This is the smart charging application of Jedlix, a start-up that tries to commercialise smart charging in The Netherlands (Jedlix, 2017). This application is an example of the way of communication between the EV owner and the aggregator. In this application the state of charge of the EV battery is displayed. The user can set the time of leaving, the amount of kWh that he wants and he has the opportunity to switch off smart charging completely.

Predicting the amount of electricity needed for charging

As for all electricity suppliers, the aggregator needs to balance its electricity portfolio. The electricity portfolio is the balance of the amount of electricity that a party buys and the amount that it actually uses. The aggregator does not need to be a balance responsible party (BRP, the legal entity that is responsible for balancing demanded electrical energy and actual used energy), but smart charging can only be profitable when the actual charged electricity is matching the electricity bought. This implies that the more information you have about the demanded electricity for the day ahead, the better your buying decisions[1] will be.

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[1] *Buying decisions are based on the EPEX Index that can be accessed on the online platform of EPEX day-ahead NL. On the EPEX day-ahead market the suppliers and bidders are informed about the current status of the auction via the EPEX Index. The EPEX*

The aggregator needs to make a prediction of the charging behaviour by analysing historical behaviour of his pool of customers. This can be done by implementing a learning algorithm that compares historical consumption data of the customers and produces a prediction of the consumption for the following day. Bigger pools of EV's have a more predictable charging behaviour than smaller pools. This is due to the statistical affect called the law of large numbers (Tversky & Kahneman, 1971). Therefore, parties that will commercialise smart charging will try to control large pools of charge points, to optimise their buying decisions.

Determining optimal charging times using spot market prices

It is concluded that the aggregator will optimise the smart charge sessions on his own portfolio purchases. When the actual charge session takes place, the aggregator already has a portfolio of purchased electricity. To balance his portfolio as much as possible the aggregator will try to match the charged electricity with the purchased electricity. This will minimise balancing costs and maximise profit.

When there are charge sessions that require more electricity than is available in the portfolio, the aggregator cannot optimise the charge sessions on the portfolio. In this case the aggregator can choose to charge in the hours with the lowest spot market prices. This way the portfolio becomes adaptive to unpredictable charging behaviour and changes in spot market price characteristics.

2.3 Increased demand on spot market due to charging

This section is dedicated to the third sub question: How can the increase in spot market demand due to charging be estimated?

Due to the increase in EV's in The Netherlands, the electricity demand will increase depending on the charging behaviour of the drivers. Because the ABCD model is simulating the charging behaviour of EV owner, the model is suited to simulate the demand increase on spot markets. To determine this shift in demand,

The charging load with and without smart charging is simulated with the ABCD model in neighbourhoods. This charging demand could be translated to a change in national demand with the right translation algorithm.

There are two differences between the charging demand in a neighbourhood and the charging demand for The Netherlands. Firstly, the amount of kWh charged needs to be scaled depending on the ratio of amount of cars in the neighbourhood and the amount of cars in The Netherlands. Second, the charging demand in the neighbourhood will have more variation than the charging demand of The Netherlands due to the statistical effect of larger numbers.

Instead of simulating a large group of EV's, this statistical effect can also be estimated by taking the average charging demand of a smaller group of EV's over multiple days. After a representative charging demand has been created, the demand can be scaled with a multiplication factor.

End of chapter 2: Modelling Approach

Index is a time average price index to serve market players and can be used as a reference price for spot electricity (EPEX SPOT, 2016).

3 Model development

This chapter elaborates on the development of the smart charging module. As was mentioned in the introduction, the module is divided into three boxes that correspond to the three sub questions. This chapter follows the structure of the module boxes. All the programming is performed in GAMA.

3.1 Box 1: electricity spot market

BOX 1 simulates spot market prices that can be used for smart charging. Fig. 6 shows a flowchart of BOX 1 of the smart charging module. Firstly, a supply curve is constructed in BOX 1, as indicated by the flowchart. The two methods to construct a supply curve discussed in chapter 2 are used in the smart charging module. The user of the ABCD model can choose which of the two methods is used for the price calculations. Secondly, the intersection of the supply and demand is determined in the smart charging module.

The electricity supply and demand of the generators are inputs of BOX 1 and these parameters can be changed depending on the scenario preferences of the user. The spot market prices will be calculated for the day ahead in the model simulation, similar to the price index on a day-ahead spot market. Like a day-ahead market, the market opens at 00:00 every day and closes at 23:59. When the market is opened, the spot market prices for the next day and the current day are accessible in the simulation.

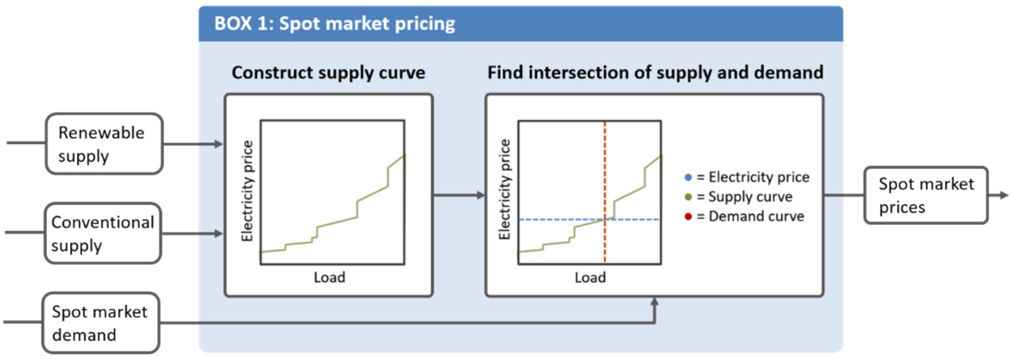

Fig. 6 Flowchart of BOX 1 of the smart charging module. The module generates spot market prices with the inputs renewable supply, conventional supply and spot market demand. The renewable supply and conventional demand are used to construct a supply curve. Thereafter, the intersection is found between the supply curve and the electricity demand in a specific hour. The intersection price is the price of electricity in that specific hour.

Supply curve based on installed conventional generation capacity and SRMC

The SRMC of coal plants, CCGT, CHP and older gas plants are calculated in BOX 1 using the CO_2 prices, coal prices and gas prices. O&M costs are considered insignificant and are therefore not taken into account. The SRMC data is gathered from ECN from 2016 until 2035 (Schoots, Hekkenberg, and Hammingh 2016). The SRMC of nuclear and renewables are considered constant because uranium prices vary less and short run marginal costs of renewables are nearly zero. Also, the electricity prices are nearly never depending on these SRMC, because this only happens in hours with extremely low demand in the coming years. The data is also gathered from ECN (Seebregts et al. 2009a). The cost curves from 2016 until 2035 can be found in Appendix 8.2.

For some generator types the SRMC per generator varies a lot. For instance the SRMC of gas turbines is very dependent on how old and how big the turbine is. To take this into account, the highest SRMC and the lowest SRMC of these generator types are calculated. The SRMC of the generators in between are estimated by linear interpolation between these lowest and highest SRMC.

The supply capacities of the conventional generators are gathered from ECN as well (Seebregts et al. 2009b; Ybema et al. 2012). The renewable supply is calculated by multiplying hourly average weather data of the KNMI (KNMI 2016) with the installed capacities of wind and PV according to equations (2), (3) and (4). It is assumed that rated power is reached at 80% of the maximum measured wind speeds.

$if\ wind\ speed\ 10m_{normalised} < 0.8$:

$$production_{wind} = wind\ speed\ 10m_{normalised} * \ installed\ cap_{wind} \tag{2}$$

$if\ wind\ speed\ 10m_{normalised} \geq 0.8$:

$$production_{wind} = installed\ cap_{wind} \tag{3}$$

Where *wind speed 10m$_{normalised}$* is the KNMI hourly average measured wind speed in De Bild at 10 meters height normalised, the *production$_{wind}$* the hourly wind production and the *installed cap$_{wind}$* the installed capacities for onshore and offshore wind. For PV production we have:

$$production_{PV} = \ solar\ irradiance_{normalised} * installed\ cap_{PV} \tag{4}$$

Where *solar irradiance$_{normalised}$* is the KNMI hourly average measured solar irradiance in De Bild normalised, the *production$_{PV}$* the hourly PV production and the *installed cap$_{PV}$* the installed capacities for PV in The Netherlands.

For renewable supply the installed capacities are assumed to be the same as the renewable energy targets as stated by the Dutch government (Schoots, Hekkenberg, and Hammingh 2016). All the installed capacities from 2016 until 2035 that are gathered are shown in Table 3 in Appendix 8.3.

Supply curve based on relation between demand and spot market prices

As was mentioned in chapter 2 there is both a linear trend as an exponential trend defined for the relation between conventional supply and electricity prices. The relation between the spot market prices and the conventional supply is depending on the SRMC and supply capacities of generators. To make the supply more adaptive to changing SRMC and supply capacities, the constants in the equations can be replaced by functions that depend on the SRMC and supply capacity that is available.

Equation (6), (5) and (7) show the functions that are used in BOX 1 as fitted supply curve. Equation *y1* is the fitted linear trend for conventional supply, *y2* the exponential trend that compensates for expensive gas turbines with market power and *y3* is the function for renewable and coal supply.

$$y1 = {(SRMC_{CHP} - SRMC_{new\ coal})}/{(CCGT + CHP)} * (demand - RENWABLE) - 9.72 \tag{5}$$

And for *demand* > *RENEWABLE* + *COAL*:

$$PRICE = \ y2 = \ e^{(0.0008 * (demand - (RENEWABLE + COAL + CCGT + CHP))} + y1 \tag{6}$$

And for *demand* ≤ *RENEWABLE* + *COAL*:

$$PRICE = y3 = {(SRMC_{new\ coal})}/{(RENEWABLE + COAL)} * demand \qquad (7)$$

Where *PRICE* (€/MWh) is the spot market price for a specific hour, *y1* the fitted linear function, *y2* is the fitted exponential function, *demand* the spot market demand, *RENEWABLE* the renewable supply on the spot market, *COAL* the coal supply on the spot market, *CCGT* the CCGT supply and *CHP* the CHP supply. The *SRMCs* are the short run marginal costs for the generators. All the production is in units of MWe and SRMC are in units of €/MWh. The functions *y1*, *y2* and *y3* are plotted in Fig. 7.

The function *y2* is only defined for conventional generation from CCGT until old gas turbines. As can be observed in the equations, the function is shifted over the X-axis depending on the amount of renewable and coal supply. Function *y3* is defined for renewable and coal generation. The function is adjusting its slope when renewable and coal supply is changing so that *y2* = *y1* at *demand* = *RENEWABLE* + *COAL*.

The combination of the fitted curve *y2* for conventional generation and the flexible curve y3 for renewable generation makes it possible to predict spot market prices with changing renewable generation. Currently, *y3* is also defined for coal supply and thus not completely depending on renewable supply. The reason for this is that the function *y2* would become negative for coal supply, which is not a valid SRMC of coal. The discussion elaborates further on this issue.

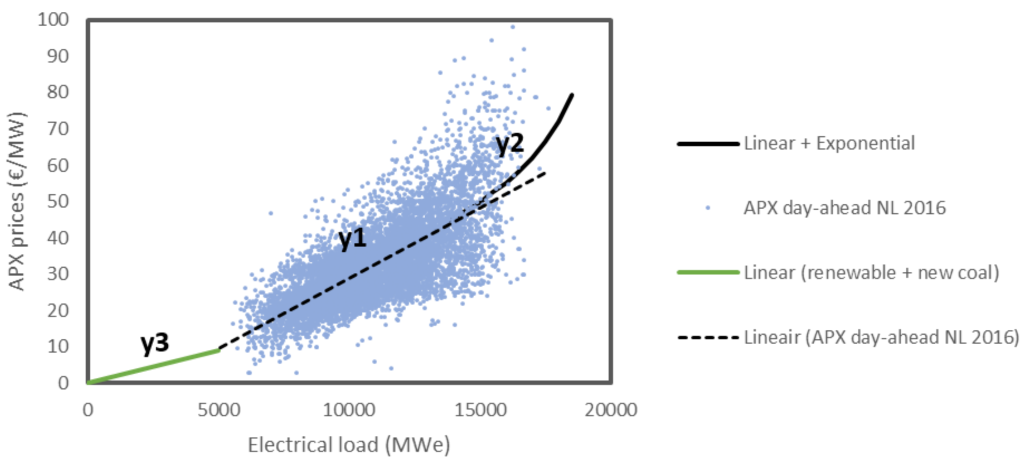

Fig. 7 The APX day-ahead prices plotted against the hourly demand with the 3 equations that constitute the supply curve. In this case there is no renewable supply, which would shift the trends to the right side. Equation Y2 is used as supply curve for conventional supply and Y3 for renewable supply and new coal generation.

3.2 BOX 2: smart charging

BOX 2 of the smart charging module is communicating with the charge points in the ABCD simulations to enable smart charging.
Fig. 8 shows a flowchart of BOX 2. The electricity prices of BOX 1 are used to create optimal charge schedules which are send to the charge points. An agent called “aggregator” is created in GAMA to perform the calculations.

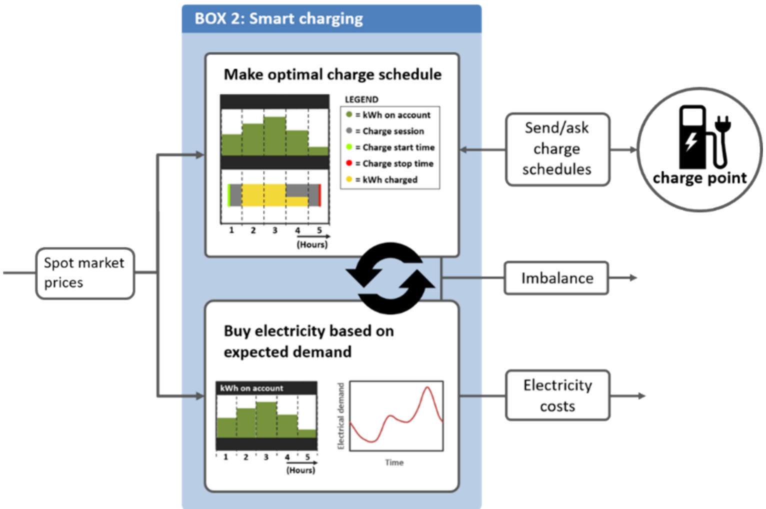

Fig. 8 BOX 2 of the smart charging module. The BOX is constructed out of two main parts, the top part is making optimised charge schedules and the bottom part is buying electricity for charging based on expected charging demand.

When an EV is connected to a smart charge point in the neighbourhood, the charge point will collect the charging constraints from the EV owner. The charging constraints are the charge need (amount of kWh that need to be charged), charge speed (in kW) and the time frame in which he wants to charge (the current time and the time he wants the EV to be ready). The charge point sends the charging constraints to the aggregator which will make an optimal charge schedule for the EV.

Creating optimal charge schedules

The top component depicted in
Fig. 8 is responsible for creating optimal charge schedules for the EVs in the simulation. Ones the charging constraints of the charge session are send to the aggregator by the charge points, the aggregator can perform the optimisation.

The optimisation can be performed on the portfolio of the aggregator or on the spot market prices, as was explained in chapter 2. In first instance, the electricity that is bought by the aggregator is used for the optimisation. If there is no electricity left over on the account of the aggregator, the optimisation will be performed with the spot market prices of the current day.

Fig. 9 shows an example of an optimisation using both the bought electricity and the electricity prices as optimisation vector. In every iteration, the most optimal hour is chosen to fill the charge schedule. In the first case, the optimal hour is defined by the hour where the most kWh are on the account of the aggregator. In the second case, the optimal hour is defined by the cheapest hour in the time frame of the charge session. The optimisation ends when either the charge need is satisfied, the whole charge schedule is full or the EV is disconnected from the charge point.

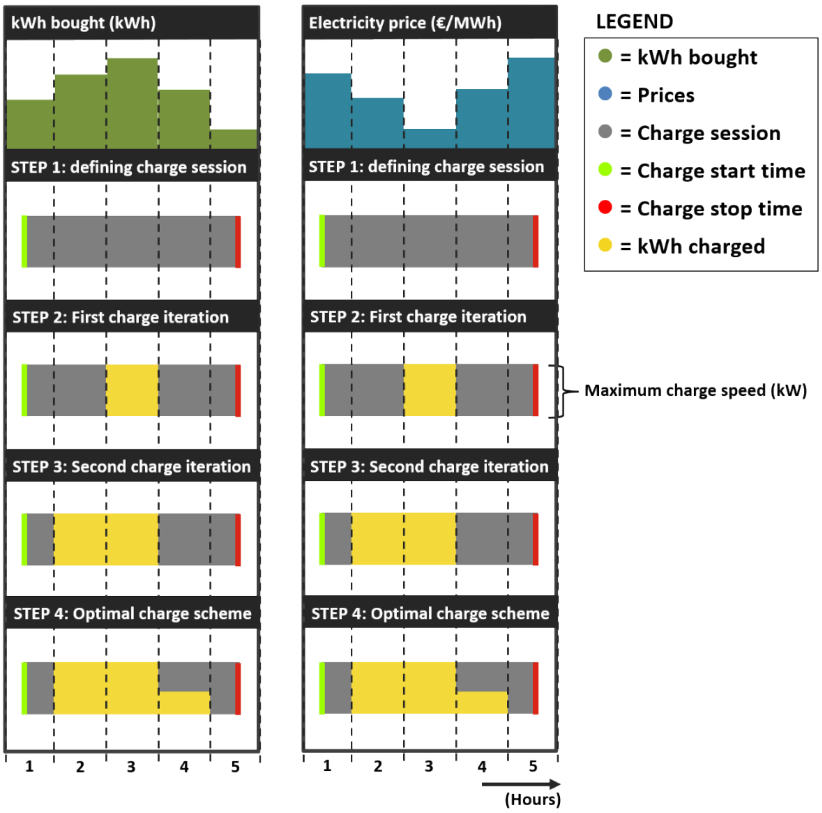

Fig. 9 Example optimisation as performed by the algorithm used in BOX 2 of the smart charging module. The amount of iterations depends on the length of the charge sessions and the charge requirements of the EV owner.

Buy electricity based on expected charging demand

As depicted in

Fig. 8, the second component of BOX 2 is calculating expected charging demand and buying electricity for the day ahead. As was explained in chapter 2, the aggregator needs to make a prediction on how much kWh will be needed for the charge sessions of the following day. The expected charging load is calculated with a serial weighted average as is formulated by equation (8).

$$expected\ load_{day\_i} = \frac{weight * expected\ load_{day_i - 1} + \ todays\ charging\ demand}{weight + 1} \tag{8}$$

Where *expected load* (kWh) is the array with the expected charging load for every hour of the day ahead, *day_i* is the current day, *weight* is a constant chosen by the modeller that determines the weight of the historical charging demand and *todays charging demand* (kWh) is the array with the charging demand for every hour of the current day.

The amounts of kWh indicated by the expected charging load array are directly bought from the spot market. This is process is repeated every midnight in the simulation to update the kWh that are on the account of the aggregator that can be used for smart charging. The charging costs are also calculated taking the sum of the components of the buying array.

3.3 BOX 3: demand shift due to charging

As discussed in section 2.3, the load shift is depending on two factors. Firstly, a load curve of a representative group of EV users in The Netherlands. Secondly, a scaling factor depending on the ratio between the amount of cars in The Netherlands and the amount of cars in the neighbourhood. This relationship is expressed by equation (8).

$$Demand\ shift = average\ load\ curve * scaling\ factor \tag{8}$$

Where the *demand shift* is a vector with 24 elements in kWh for every day of simulation, the *average load curve* also a vector with 24 elements in kWh for every day of simulation and the *scaling factor* a ratio.

The weighted average load curve of the ABCD simulation is used as *average load curve*. The weighted average load curve is calculated using equation (9) in the previous section. The scaling factor is calculated according to equation (9). Currently, the amount of cars in The Netherlands is approximately 8 million. The average neighbourhood has 500 cars which makes the order of the scaling factor approximately 10^4.

$$Scaling\ factor = \frac{amount\ of\ cars\ in\ NL}{amount\ of\ cars\ in\ the\ neighbourhood} \tag{9}$$

End of chapter 3: Model Development

4 Model validation

The validity of the model is examined by relating the outputs the module boxes to their inputs in scenario analyses for every module box. Some of the results can be compared to literature to examine the validity. The analysis setup is discussed, the analysis results are presented and the results are discussed.

4.1 BOX 1 validation

Firstly, prices calculated with both the methods used to construct BOX 1 are compared with the 2016 APX day-ahead prices. There are two measures that are compared: (1) the average price per hour and (2) the root mean squared error (RMS) of the price curves relatively compared to their own average price. The average RMS is a measure for the volatility of the price curves. It is calculated by taking the average of the distances between every point and the daily average price, as indicated by equation .

$$RMS = \frac{1}{N}\sum_{i=0}^{N}\sqrt{(daily\ average\ price_i - price_i)^2} \qquad (10)$$

Where N is the amount of hours in a year, $price_i$ is the price in the i^{th} hour and the *daily average price$_i$* is the average price of the corresponding day. The average price per hour and the volatility are the most influential parameters for smart charging of the price curves.

The simulations are run over the whole year of 2016. Hourly average data of supply and demand are used from the year 2016. Thereafter, 2025 spot market prices are simulated with the fitted supply. This allows to examine the influence of changing supply on the generated day-ahead prices by BOX 1. Detailed information about the installed capacities, SRMC and spot market demand data can be found in Appendix 8.2, 8.3 and 8.4.

Validating 2016 spot market prices and analysing 2025 prices

Fig. 10 shows the average spot market prices for the APX 2016 day-ahead market, 2016 simulated prices with the ECN supply curve, 2016 simulated prices with the fitted supply curve and 2025 simulated prices with the fitted supply curve. Also, the average RMS values of the price curves are indicated in the legend of the figure.

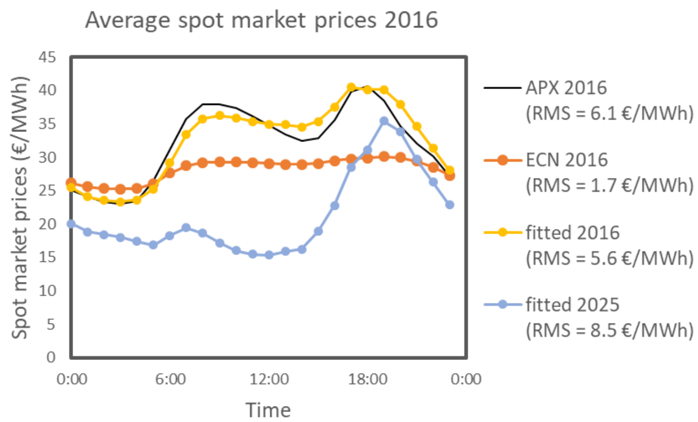

Fig. 10 Electricity prices generated by BOX 1 compared to the real APX prices in 2016 and 2025 prices generated with the fitted supply curve. The volatility of the curves is expressed in their average RMS value that is displayed in the legend.

The 2016 prices generated with the ECN supply curve shows peak and valley prices during the same hours as the APX price curve. However, on average the prices are lower than the APX prices and show less volatile behaviour over the day. Apparently, the slope of the ECN supply curve is not steep enough, which implies that there is too much generation capacity available. This makes sense if one notes that the ECN supply curve is constructed with all the Dutch installed generation capacity, while not all generated electricity is traded on the spot market. The fitted supply curve is constructed to improve the simulated prices with BOX 1.

The average of the 2016 prices generated with the fitted supply curve and the APX prices are exactly the same. This is not surprising, because the fitted supply curve is fitted on the 2016 prices. The biggest difference between the curves is observed around midday were the volatility of the APX prices in higher than the simulated prices. This effect could be related to the characteristics of steam turbines. Because starting up or ramping up is more costly than stable generation, the SRMC of these generators might drop slightly during midday. Also, the variation in air temperature during the year increases the variation in efficiencies of generators and therefore also SRMCs. This is not taken into account in the fitted supply curve.

The 2025 prices generated with the fitted supply curve are on average lower than the 2016 prices. This is due to more renewable generation and the prediction that there will still be coal generation available in this year. If this prediction is true it means that expensive gas generators will be pushed out of the merit-order and prices are mostly determined by cheaper coal generation. However, the volatility of the curve increases compared to the 2016 prices, mostly because of the intermittent characteristic of renewable generation.

4.2 BOX 2 validation

To validate BOX 2, six scenarios are compared with two baseline scenarios as presented in Fig. 11. In the scenarios, one input is changed compared to the baseline scenario to analyse the independent effect of the variable. The impact of more EV, more renewables and a different season are assessed. The impact of more EV is mostly influencing the load on the grid. More renewables and different seasons determine the spot market prices. Therefore they determine the cost effectiveness and the interaction between renewable generation and smart charging. All the scenarios are run for both normal charging as smart charging, to be able to see the effect of smart charging.

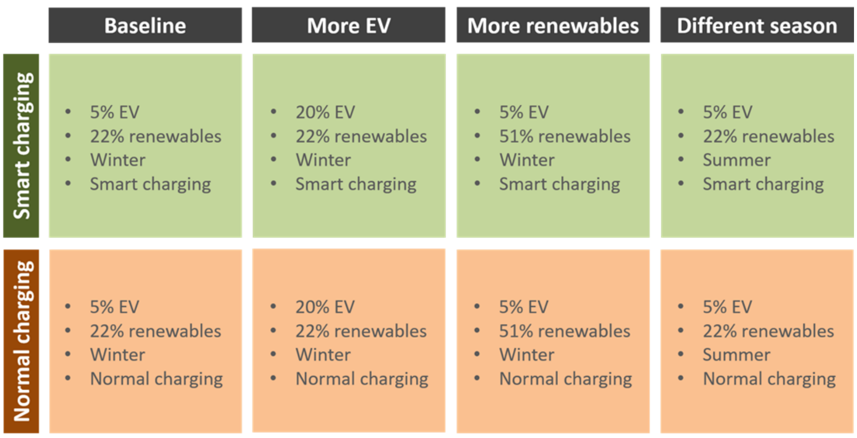

Fig. 11 Eight scenarios used for the validation of BOX 2. The top scenarios are with smart charging and the bottom scenarios are with normal charging to compare the relative impact of smart charging on the outputs. To see the influence of the prices and the amount of EV on the outputs of BOX 2 the amount of EVs is varied from 5% to 20% and the amount of renewables is varied from 22% to 51% installed capacity. Also, to see the difference between seasons, the most right scenarios are run with demand and renewable generation adapted to the summer instead of winter.

To see the influence of the amount of EVs in the neighbourhood, the percentage households with and EV is varied from 5% to 20% in the neighbourhood (2017 and 2025 percentages predicted by the ABCD model). These percentages resemble the percentage of households with an EV in the neighbourhood. The amount of commuters working in the neighbourhood is assumed to be the same.

To see the influence of the prices on the outputs of BOX 2 the amount of renewables is varied from 22% to 51% installed capacity. These percentages resemble the amount of renewables in The Netherlands in 2017 and 2025, predicted by ECN (Schoots, Hekkenberg, and Hammingh 2016). And lastly, to see the difference between seasons, the most right scenarios are run with demand and renewable generation data corresponding to the summer instead of winter.

The amount of charge points in the neighbourhood is automatically adjusted for the amount of EVs. It is assumed that every resident that owns an EV gets either a charge point at home or a public charge point near his house. The public charge points that are installed in the neighbourhood can also be used by the commuters. The amount of work charge points at the offices is depending on the amount of commuters that work in the neighbourhood.

The neighbourhood that is used for the scenario analyses is the Zeeheldenkwartier neighbourhood in The Hague. Only weekdays are simulated in the scenarios over 30 days in one specific season. This implies that the spot market demand resembles the demand of weekdays and the wind and PV production is depending on weather data from corresponding dates in 2016. Also, the residents and commuters are going to work every day. Some residents might make evening trips with a probability of 30%. Detailed information about the installed capacities, SRMC and spot market demand data can be found in Appendix 8.2, 8.3 and 8.4.

Average electricity prices in simulations

Fig. 12 shows the average electricity prices for the scenarios. Because the amount of EVs and smart charging are not influencing the spot market prices, there are three different price curves presented. The most important difference between the price curves is their volatility, which is influencing the smart charging costs for a major part. The peak prices and valley prices are nearly in the same hours, which means that the times of smart charging will be comparable.

Charging load on the local grid

The load on the local grid is presented as an hourly average in Fig. 13. The scenarios with 5% EVs have nearly the same charging load of around 100 kWh and show similar charging behaviour over the day. In the scenarios with 20% EV the charging load is around 400 kWh (4 times higher), which corresponds to the increase in EVs. The charging behaviour also changes in the normal charging scenario, because commuters charge relatively more at work during the morning.

In the normal charging scenarios the residents charge when they arrive home from work in the late afternoon and the commuters charge when they arrive at work in the morning. The average time residents arrive at home is 16:30 in these scenarios, which is defined in the ABCD model as the arrival time. The peak loads are therefore depending on the times that the people are working and there is little demand during the night.

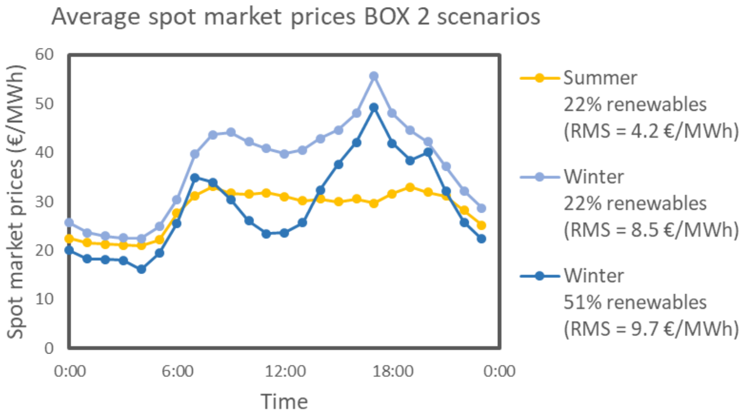

Fig. 12 Average electricity prices using the fitted supply curve for a summer with 22% renewables, a winter with 22% renewables and a winter with 51% renewables. The amount of renewables is expressed as percentage installed capacity and based on ECN predictions for 2017 and 2025. The volatility of the price curves is expressed in average RMS values in the legend. In the "summer 22%" and the "winter 51%" the average price lies around 28 €/MWh. In the "winter 22%" the average price lies around 35 €/MWh. The volatility is the lowest for the "summer 22%" and the highest for the 'winter 51%".

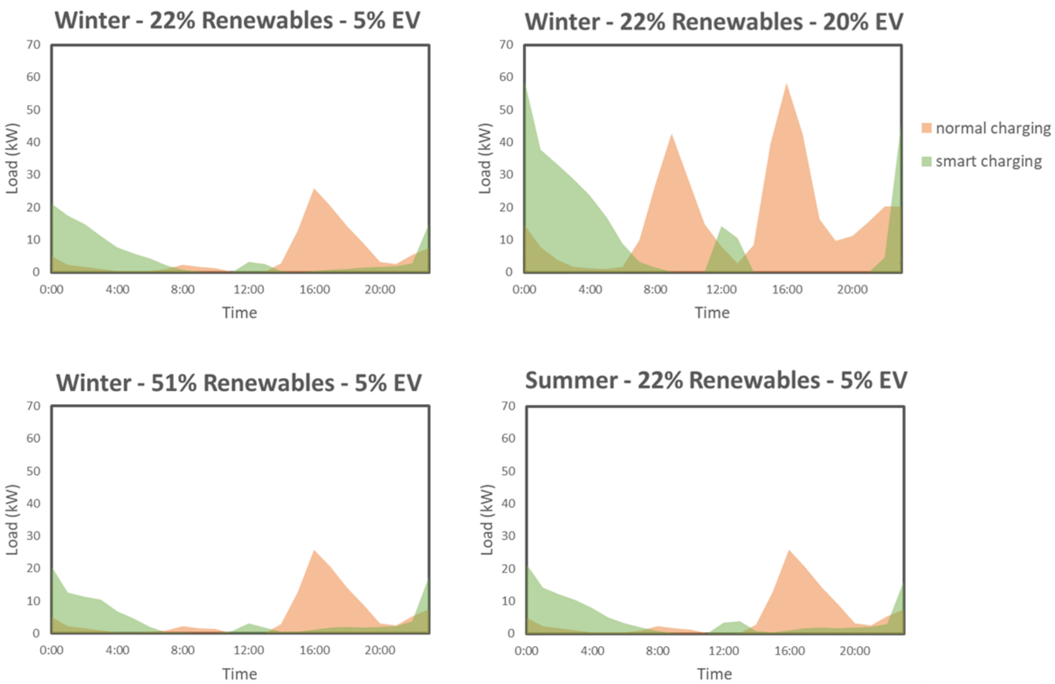

Fig. 13 Average local charging load in neighbourhood over one day in eight different scenarios. The scenarios with 5% EVs have nearly the same charging load of around 100 kWh and show similar charging behaviour over the day. In the scenarios with 20% EV the charging load is 4 times higher, which corresponds to the increase in EVs.

In the smart charging scenarios the charging load shifts mostly to midnight, because the price curves have a minimum during the night. Some of the load is also shifted to the midday, when the price curves have a local minimum. These charge sessions correspond to commuters that are smart charging during work hours. One would expect more charging load during these sessions, but due to a bug in the ABCD model at this moment, the commuters stop charging during work hours before they should. Also, one would expect to see a load peak for smart charging at 4:00 and not at 00:00. The reason for this is a bug in the buying module. The discussion elaborates on these problems.

Charging costs

The average charging costs per day for the eight scenarios are presented in Fig. 14. Also, the total savings over the month by applying smart charging compared to the normal charging scenarios is presented in the graphs. The first four days of the simulation are not taken into account in the calculation for the cost savings, because the expected charging demand needs four days to become a good prediction.

It can be observed that the charging costs in the normal charging scenarios are higher than the charging costs in the smart charging scenarios. This is expected because the charge sessions in the smart charging scenarios are mostly during the night when electricity prices are lower. The difference between the costs of bough electricity and charged electricity in the smart charging scenarios is minor and the average costs are nearly the same. The difference between the two becomes smaller with more EVs, which shows that more EVs make it easier to predict the correct charging load for the next day. Also, the variation in charging costs becomes smaller with more EVs.

The savings in the summer are significantly less than the savings during the winter. This can be explained by the difference in price volatility during these seasons. The low volatile summer makes smart charging less effective for decreasing charging costs.

A striking result is that the savings barely increase with more renewables. This implies that the amount of renewables does not influence the savings that much, although the volatility of the price curve with 51% renewables is significantly more volatile than with 22% renewables. One would expect volatility to be the main driver for savings made by smart charging. The reason for this striking result could be that the aggregator in the smart charging module does not make optimal buying decisions, which reduces the savings that can be made with smart charging.

Renewable electricity charged

The percentages of renewable charged electricity in the eight scenarios are presented per generator in Fig. 15. The division makes it possible to see the partial contribution of the generators to renewable charged electricity. The relative change in renewable charged electricity between the normal charging scenarios and the smart charging scenarios is also presented in the graphs.

In the winter scenarios, more renewable electricity is charged with smart charging. This effect is mostly due to charging more wind energy, because the PV production is minor in the winter months. An increase in EVs has a minor influence on the amount of renewable charged electricity, except PV is charged more in the normal charging scenario by charging at work. The percentages renewable charged electricity in the scenarios with 51% renewables are higher, but the total increase in renewable charged electricity is similar to the other winter scenarios.

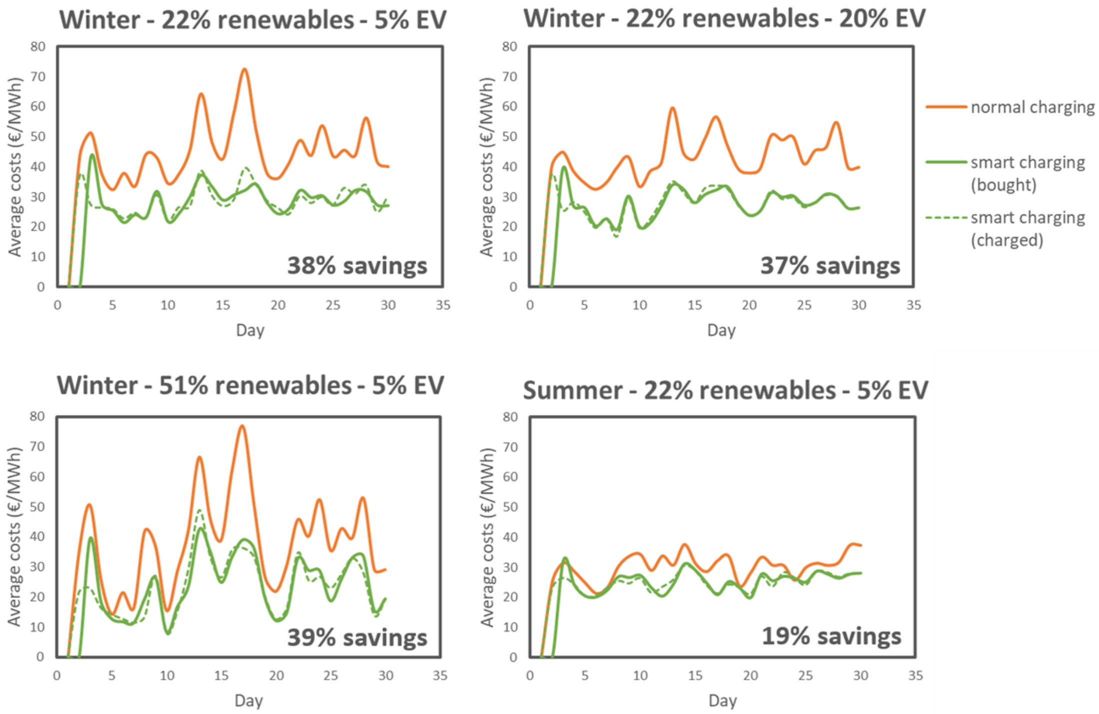

Fig. 14 Daily charging costs for the month of simulation in the eight different scenarios. For smart charging the costs for bought electricity and the cost of charged electricity are displayed. It shows the difference in the expected charging demand and the actual charged electricity. The savings are calculated by comparing the costs for bought electricity with the normal charging costs.

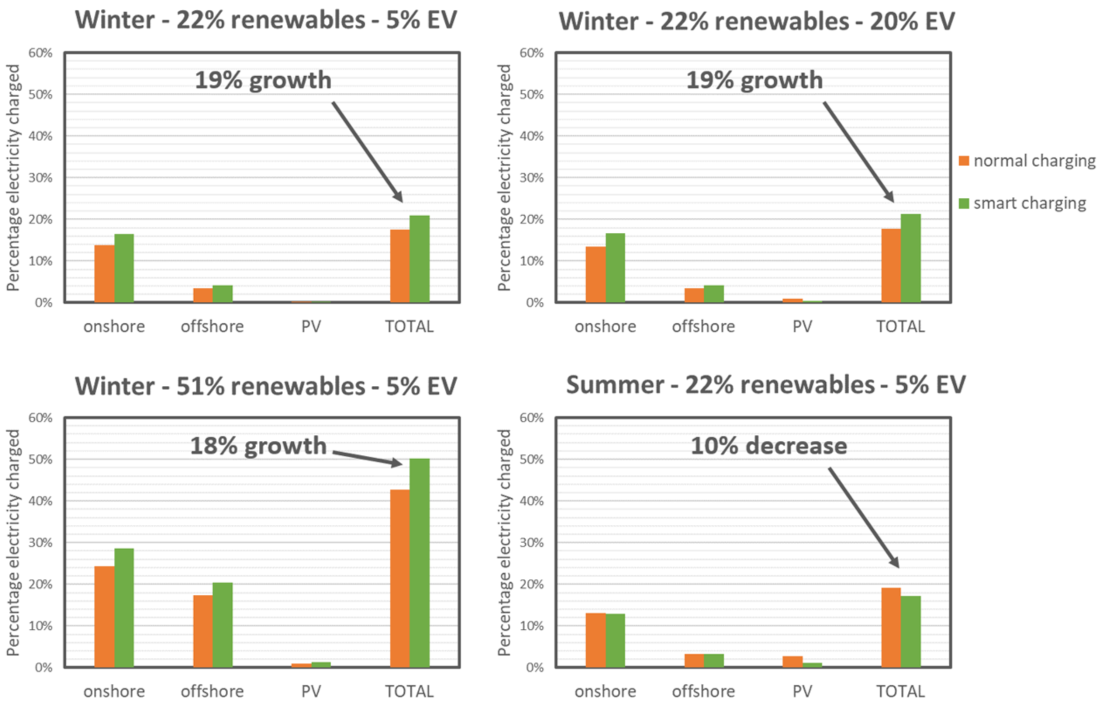

Fig. 15 Percentage renewable charged electricity per generator and for the total renewable generation. The percentages indicate the change in the total amount of renewable electricity charged from the normal charging scenarios to the smart charging scenarios.

For the summer scenario, the percentages renewable charged electricity are lower with smart charging. Although this result is striking, it can be explained in two steps. Firstly, due to a big in the ABCD model, commuters do not charge as much at work as they should (elaboration in the discussion). Therefore, less electricity is smart charged during midday when the sun shines.

Secondly, both PV production and wind production are higher during the day compared to the night. For PV production this is a straightforward statement, but for wind energy it is not. However, the results imply that wind energy is correlated to the time of the day. This effect can be explained by looking at the relations between average wind speeds, time of the day and height in Fig. 16 (following section). The wind speeds measured on 10 m above ground are higher during the day. The KNMI data that is used is measured at a height of 10 meters and shows the same trend as in Fig. 16.

Wind production is more likely to be higher during the night because the hub heights of wind turbines are above 70 meters. Thus, if the correct wind production would be used, more wind energy would be charged with smart charging, compared to the current results.

4.3 BOX 3 validation

The scenarios used to validate BOX 3 are based on 5 questions that are currently relevant issues for different stakeholders. Therefore, this scenario analyses can be used to validate BOX 3, but also to give insight into the application of the smart charging module. The 5 stakeholder questions that are answered with the scenario analysis of BOX 3 are:

Electricity supplier: How much charging load in the neighbourhood is flexible due to smart charging?
Local grid operator: When do load peaks occur and how high are these load peaks in the neighbourhood when smart charging is applied?
EV owner: With what percentage are the charging costs reduced when smart charging is applied?
Dutch government: What is the percentage increase in charged renewables when smart charging is applied?
Energy investor: What is the percentage increase in revenue for renewable generated electricity sold on the day-ahead spot market when smart charging is applied?

The four scenarios that are constructed to answer these questions for the years 2017 and 2025 are presented in

Fig. 17. The top two scenarios are with smart charging and the bottom scenarios are with normal charging. The left scenarios are a 2017 case and the right scenarios are a 2025 case with more EVs and renewable generation. Similar to the validation of BOX 2 the percentage EV is the percentage of households with an EV. The percentage renewables is the percentage installed capacity in The Netherlands. The amount of commuters working inside the neighbourhood is similar to the amount of residents with an EV. Detailed information about the installed capacities, SRMC and spot market demand data can be found in Appendix 8.2, 8.3 and 8.4.

To validate BOX 3, the results of the scenarios are linked to the inputs. The most important results that validate BOX 3 are the demand shift on national due to charging and the change in spot market prices. The two inputs that have the largest impact on these results are the price curve volatility and the percentage of EVs. Therefore, the defined scenarios can also be used for the validation of BOX 3.

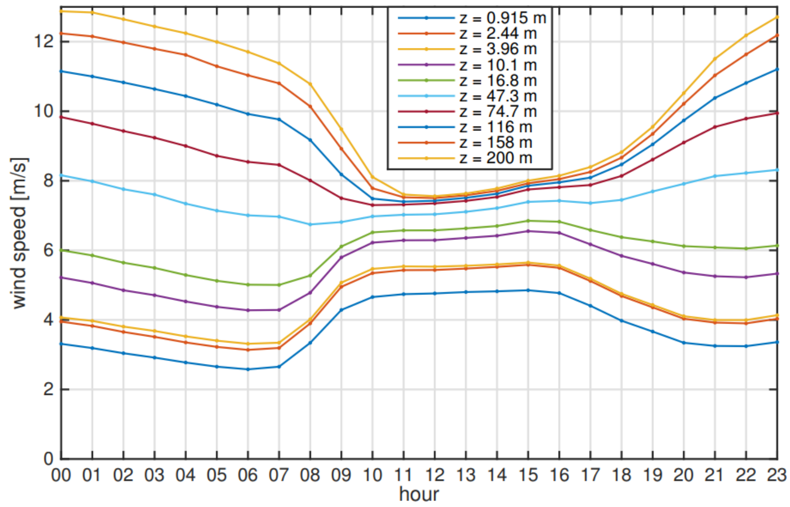

Fig. 16 Average wind speeds during the day on different heights (Kelley and Ennis 2016).

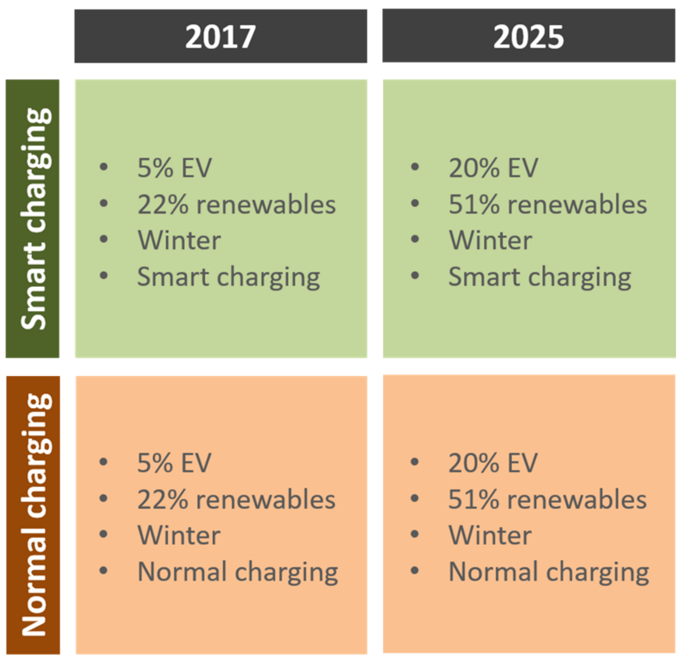

Fig. 17 Scenario quadrants for the scenario analysis of BOX 3. On the bottom the normal charging scenarios are presented where only normal charging is applied in the neighbourhood. On the scenarios on the top all the charge sessions are performed with smart charging. In the left scenarios the amount of EVs and renewables are related to a 2017 case. In the right scenarios the amount of EVs and renewables are related to a 2025 case. The percentages of renewables are installed capacities.

Average spot market prices

Fig. 18 shows the average market prices for the scenario quadrants compared to the average prices generated without influence of EV charging. The average prices in 2017 are higher than the average prices in 2025 due to more renewable production. The higher renewable production is also increasing the volatility of the price curves from 2017 to 2025.

The impact of EV charging demand on the spot market prices can be observed by comparing the coloured lines with the black line. EV demand is increasing the price in all scenarios. However, in the normal charging scenarios the peak prices increase and in the smart charging scenarios the valley prices increase. The increase in peak prices is already visible in the 2017 normal charging scenario, where the peak price increases from 57 €/MWh to 65 €/MWh. In 2025 the influence of EV charging has a major impact with peak prices increasing over 25%.

The increase in prices in the smart charging scenarios is lower than the increase in the normal charging scenarios. Therefore, the average prices with smart charging are lower than with normal charging. In 2017 the average price decreases with 1.4% and in 2025 with 5.6% with smart charging. This effect is caused by the non-linear relationship between price and demand used in BOX 1. At times of low demand and high renewable generation, the slope of the supply curve is low. At times of high demand and low renewable generation, the slope of the supply curve is steep.

Load on the local grid in Zeeheldenkwartier, The Hague

The load on the local grid is presented as an hourly average in Fig. 19. The average load for 200 households is plotted in the graphs to see the relative impact of EV charging on the load in the neighbourhood. Also, the average amount of shifted load per day is presented.

The relative increase of the load in 2017 is minor and will not worry grid operators to much. However, in 2025 the peak load in the normal charging scenario increases from 160 kW to 220 kW, which is a significant increase. When smart charging is applied both in 2017 and 2025 the peak load is not changing. However, when more than 30% of households have an EV, smart charging can create a new load peak during the night, because the spot market prices are lowest during the night.

The total amount of load that can be shifted on average per day in 2017 is 3.7% of the total load on the local grid. In 2025 this is 11.6% on average per day. This is more than 90% of the total charging load per day, which indicates an enormous flexibility in charging. This confirms the potential to use smart charging for electricity suppliers to balance their electricity portfolios.

Demand shift on national level due to charging

These results show the effect of BOX 3 on the spot market demand. Fig. 20 shows the average demand shift on national level for the four scenario quadrants. The hourly average demand of 2016 is also plotted to compare the impact of EVs on the national demand.

In 2017 the average demand increase per hour is 1.2% and in 2025 it is 4.2%, which shows that EV have a marginal impact on the national demand. The difference between 2017 and 2025 can be explained by the increase of EV's from 5% to 20%. The most important difference between the normal charging scenarios and the smart charging scenarios is that the demand increase in the normal charging scenarios increases the peak demands, while in the smart charging scenarios only the valley demand is increased. This is the same difference that was observed in the local charging load of Fig. 13.

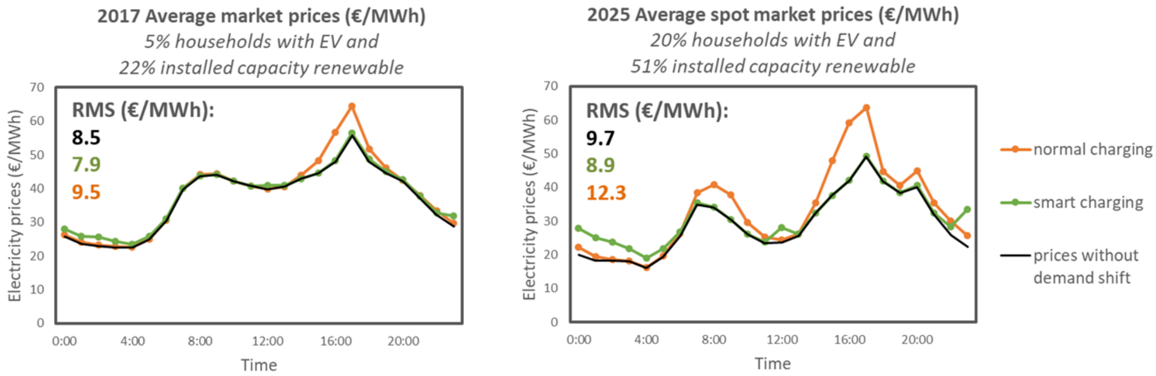

Fig. 18 Average market prices for the normal charging scenarios, smart charging scenarios and the prices without demand shift due to charging. The change in spot market prices due to an increase in charging demand is visible by comparing the black line with the coloured lines.

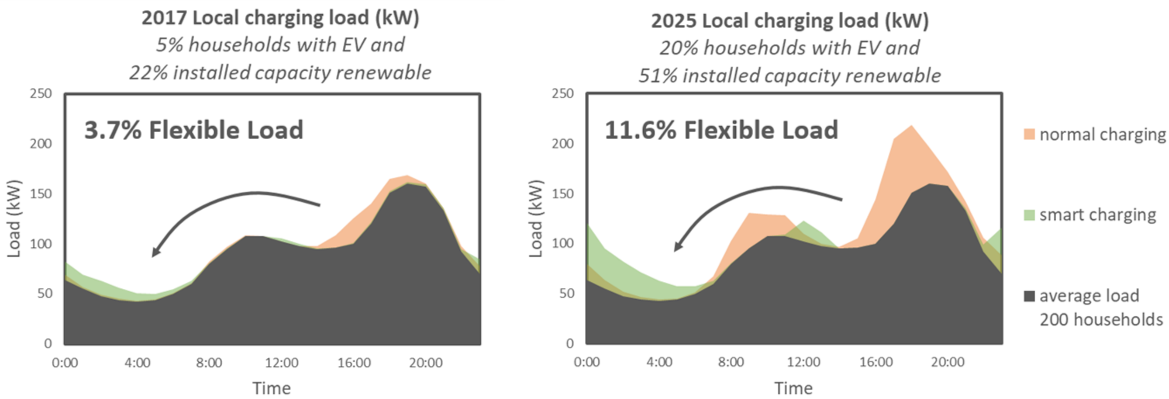

Fig. 19 Average local charging load in neighbourhood over one day. The average load for 200 households is plotted in the graphs to see the relative impact of EV charging on the load in the neighbourhood. In 2017 3.7% of the total load in the neighbourhood can be shifted on average with smart charging from the late afternoon to the night. In 2025 11.6% of the total load can be shifted with smart charging.

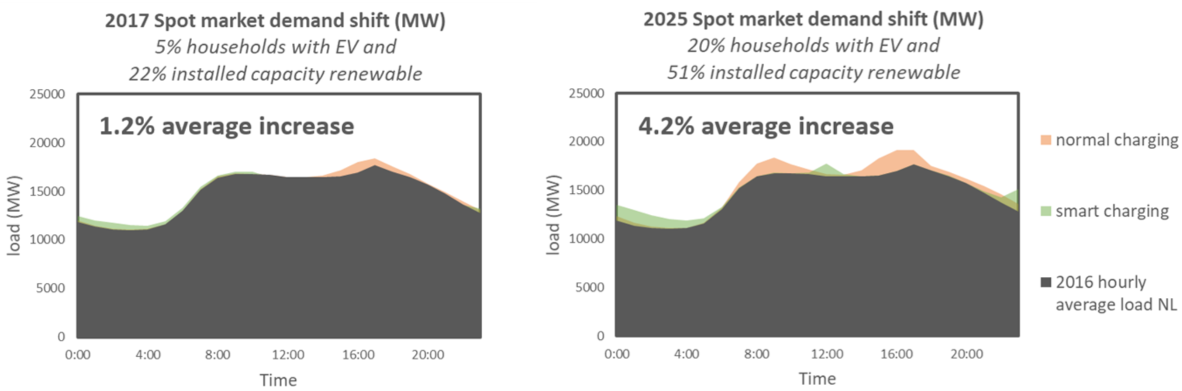

Fig. 20 Hourly average demand shift due to charging of EV's on national level compared with the average demand of The Netherlands. In 2017 the average demand increase per hour is 1.2% and in 2025 it is 4.2%. The most important difference between the normal scenarios and the smart charging scenarios is that the demand increase in the normal charging scenarios increases the peak demands, while in the smart charging scenarios only the valley demand is increased.

The demand increase that is observed in Fig. 20 is 1600 MW in the peak hours. Comparing this number with the increased load on the local network of 40 kW in Fig. 13, the multiplication factor is 1600 MW/40 kW = 40000. This number is equal to the amount of cars in The Netherlands, divided by the amount of cars in the Zeeheldenkwartier; 8000000/200 = 40000.

Charging costs in Zeeheldenkwartier, The Hague

The average charging costs per day are presented in Fig. 21. The average prices are shown over the whole month to show the variation in charging costs over one month. Also, the average percentage that is saved and the average savings in €/month per EV by applying smart charging are presented in the graphs.

An EV owner can save 6.9 €/month on charging costs in 2017 and 5.0 €/month in 2025. These numbers are independent of taxes, because taxes are payed per kWh. This shows an interesting business case for commercial parties that want to offer smart charging to their clients. It is a striking result that the electricity cost savings are going down from 2017 to 2025. This is a different result than the resulting charging costs in the validation of BOX 2. However, in the BOX 3 scenarios, smart charging is matching supply and demand on the spot market. This is decreasing the volatility of the price curves in Fig. 18, and therefore decreasing the savings that can be made by smart charging.

The peak prices on day 13 and 17 that can be observed in the normal scenarios are due to high electricity costs during these days. In the smart charging scenarios these high costs are mitigated mostly. The variation in charging costs is higher in the 2025 scenarios, which makes sense with more renewable generation.

As can be observed in the resulting electricity prices that are presented in Fig. 18, the volatility in the smart charging scenarios is becoming lower from 2017 to 2025. This is due to the charging load that is shifted to the low demand hours, which is matching demand and supply. As was stated in the introduction, smart charging is matching demand and supply, and stabilising spot market prices. However, this has a negative effect on the savings that can be made with smart charging.

Renewable electricity charged in Zeeheldenkwartier, The Hague

The percentages of renewable charged electricity are presented per generator in Fig. 22. The division per generator makes it possible to see the partial contribution of the generators. Also, the percentage increase in total renewable charged electricity is presented.

As was expected from the validation of BOX 2, more wind energy is charged in the smart charging scenarios. There is nearly no PV charged in 2017, because installed capacity is low and the simulations are performed with weather data from December. Again, due to the commuters that are not smart charging during work as much as they should, the percentage smart charged PV in 2025 is lower than the normal charging.

As was also explained in the validation of BOX 2, more wind and PV energy could be charged if more commuters would charge and correct wind data is available in the model. These adjustments could increase the percentage renewable charged electricity by approximately 10%.

What is different from the validation of BOX 2 is that the growth in 2017 is 15% instead of 19%. This difference is due to a slight shift in charging load, with a negative impact on the amount of renewable charged electricity. This type of variation is considered a random error, depending on the period of simulation. The demand shift in national level does not have any significant impact on the percentage renewable charged electricity.

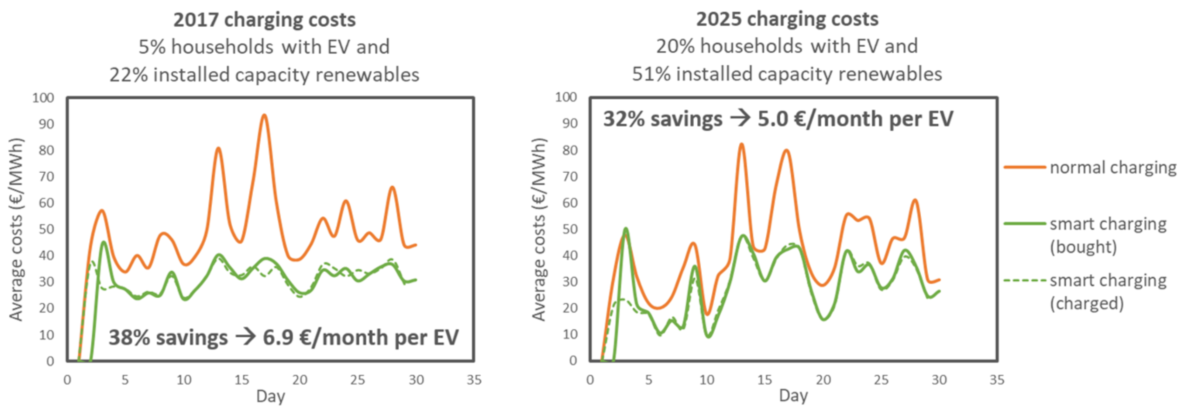

Fig. 21 Daily charging costs for one month of simulation. For smart charging the costs for bought electricity is displayed as well as the costs for the actual charged electricity. It shows the difference in the expected charging demand and the actual charged electricity. The savings are calculated with the costs for bought electricity. In 2017 38% can be saved on charging costs with smart charging. In 2025 32% can be saved on electricity costs with smart charging.

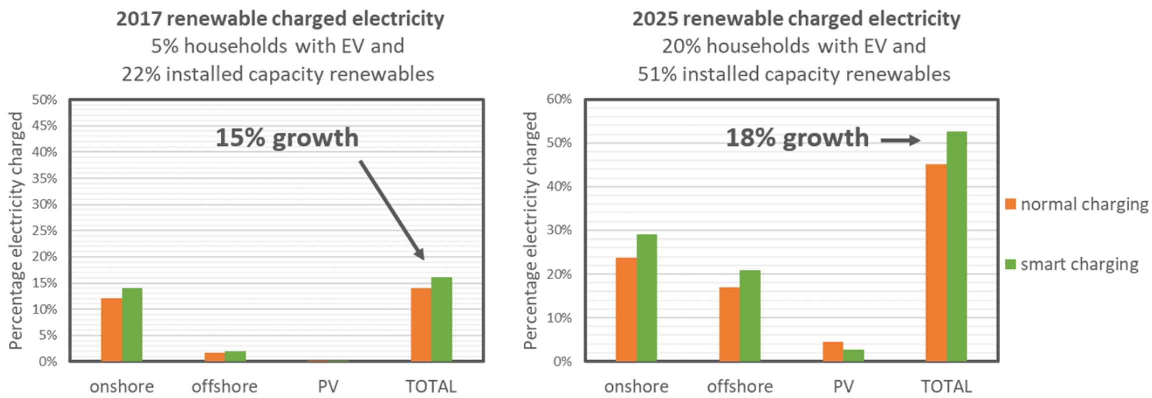

Fig. 22 Percentage renewable charged electricity per generator. The total growth in 2017 is 15% when smart charging is applied and 18% in 2025. The percentage of PV electricity that is charged is very low, because the weather data used for this simulation was of December 2016.

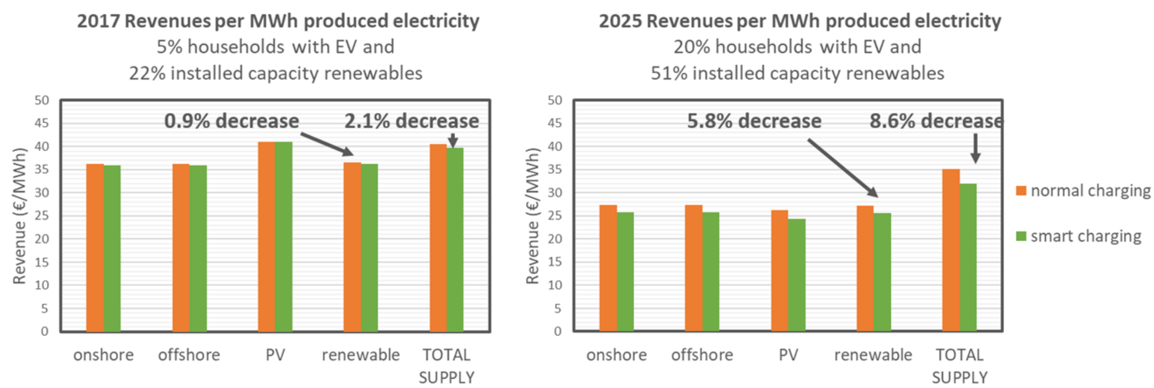

Fig. 23 Average revenues per MWh produced electricity for onshore, offshore, PV, renewable and total production. In the 2017 scenarios, the revenues for renewable generators decreases with 0.9% on average and for all the generators revenues decrease with an average of 2.1%. In the 2025 scenarios the decrease increases with an average revenue decrease of 5.8% for renewables generators and an average revenue decrease of 8.6% for all the generators. The decrease is caused by the difference in average spot market prices in the normal charging scenarios and the smart charging scenarios.

Average revenues for renewable generators

The last result of the validation of BOX 3 is showing the revenues per kWh produced electricity over the period of simulation. Fig. 23 shows these revenues for onshore, offshore, PV, renewable and total generation.

Overall, the revenues in 2025 are lower than the revenues in 2017. This is due to the lower average spot market prices in 2025 compared to 2017. For PV this effect is strongest, because the prices during midday decrease the most. Also, if the smart charging scenarios are compared to the baseline scenarios a decrease is observed. This decrease is similarly caused by a decrease in average spot market prices. The results of Fig. 23 are striking because they imply the opposite of the hypothesis that smart charging can increase the revenues of renewable generators.

The positive effect of smart charging on the revenues for renewables can be observed when the revenue decrease of renewables is compared to the revenue decrease of total generation. In 2017 the relative decrease in revenues is 0.9% for renewables and 2.1% for total supply. Likewise, in 2025 the relative decrease in revenues is 5.8% for renewables and 8.6% for total supply. The decrease for renewables is lower than for the total supply, because smart charging charges relatively more renewable electricity.

It can be concluded that the decrease in average spot market prices currently has more impact on the revenues of renewable generators than the increase in renewable charged electricity from Fig. 22. This might be a different result when more commuters are charging during work and better wind data is available.

End of chapter 4: Model Validation

5 Conclusions for stakeholders

The savings in the summer are significantly less than the savings during the winter. This can be explained by the difference in price volatility during these seasons. Currently, the low volatile summer makes smart charging less effective for decreasing charging costs. However, when more PV is installed in the future, the volatility during the summer might increase which makes smart charging more effective.

The amount of flexible load in the Zeeheldenkwartier with 5% EV is 3.7% of the total load in the neighbourhood in 2017. In 2025 this is 11.6% of the total load on average per day. This is more than 90% of the total charging load per day, which indicates an enormous flexibility in charging. This confirms the potential to use smart charging for electricity suppliers to balance their electricity portfolios.

Smart charging can decrease the load peak on the local grid with 27% when 20% of the households in a neighbourhood have an EV. With 5% households with EV , the impact of electric vehicles on the peak load is minor. When more than 30% of households have an EV, smart charging can create a new load peak during the night, because the spot market prices are lowest during the night.

The charge cost savings induced by smart charging are going down from 2017 to 2025. This effect is counterintuitive because there is more renewable generation in 2025. The reason for the decrease in savings is that there are more EVs using smart charging in the 2025 scenario. The total benefits increases, but the profit is split over more EVs, which decreases the revenue per kWh charged.

Smart charging can increase the percentage of renewable charged electricity in the winter with 18%. This percentage is not varying much in different scenarios, but is mostly depending on the season, moments of smart charging and weather. Currently, smart charging during midday is not working correctly in the model, which could increase the percentage of charged solar energy. Also, improving the onshore and offshore wind production data would increase the amount of renewable charged electricity. Also, the buying decisions of the aggregator seem to have a negative influence on the amount of renewable charged electricity.

Smart charging is significantly decreasing the volatility and the average of spot market prices. In 2017 the RMS for normal charging is 9.5 €/MWh and for smart charging 7.9 €/MWh. In 2025 with normal charging 12.3 €/MWh and with smart charging 8.9 €/MWh. In 2017 the average price decreases with 1.4% and in 2025 with 5.6% with smart charging.

The revenues for generators in 2025 are lower than the revenues in 2017. Also, revenues for generators decrease when smart charging is applied, but the impact on renewables is less than for conventional generators. The average spot market prices have the biggest impact on the revenues. The decrease for renewables is lower than for the total supply, because smart charging charges relatively more renewable electricity.

It can be concluded that the decrease in average spot market prices currently has more impact on the revenues of renewable generators than the increase in renewable charged electricity. This might be a different result when more commuters are charging during work and better wind data is available. Also, with an increasing amount of renewables in the electricity network, smart charging is becoming increasingly interesting to charge more renewable electricity.

6 Discussion

6.1 BOX 1: electricity spot market

During the development of BOX 1, spot market pricing appeared to be an extensive subject. The first supply curve that was made with the data from ECN did not give the prices comparable with reality. The reason for this could be that in The Netherlands not all electricity is traded on the APX spot market. This implies that only the supply that is being traded on the APX market should be used to construct the supply curve. This would result in a steeper supply curve, and thus, higher price volatilities and a higher price average. Since the average price resulting from the ECN supply curve is too low and the volatility of the price curve is too low, this seems to be a possible explanation.

The validation of the second method used to construct BOX 1 has an inherent problem. The supply curve for the merit-order is depending on the APX prices, and the merit-order is validated with the same APX prices. To strengthen both the construction as the validation of this method, demand curves and APX prices from different years should be used. In further research, the fitting method used in this research can be applied to multiple years. The results can be used to analyse the influence of SRMC, available supply capacity and demand on the spot market prices. This can result in better understanding of spot market pricing and better estimations for spot market prices.

6.2 BOX 2: smart charging

Currently, BOX 2 does not take into account local grid constraints in the smart charging optimisation. Local grid constraints include the line capacities, voltages and the transformer capacities. For the local grid operator it would be interesting to assess charging in the neighbourhood with these constraints included. Also, a different form of smart charging could analysed, that is optimising on minimum network load rather than lowest costs.

As was mentioned in the BOX 2 validation, the commuters stop with charging at work without reason. This decreases the charging demand during midday in the smart charging scenarios. Therefore the amount of charged solar energy with smart charging is lower than it could be in reality. To improve the results, the driving and charging behaviour of the ABCD model should be checked.

Also, the load peaks in the smart charging scenarios lie around 00:00 while the lowest spot market prices are at 4:00. The reason for this is a bug in the smart charging optimisation. Instead of using the most expensive hour in a charge session, the first hour of the charge sessions is used twice for charging. Currently, this bug is solved, but there was no time left to adjust the results. The difference in results would be that the peak in smart charging would shift from 23:00 and 00:00 to 3:00 and 4:00, resulting in lower charging costs and thus higher savings.

The KNMI wind data that was used for the wind production calculations is measured at 10 meters height. As was shown in Fig. 16 in the validation of BOX 2, the relation between daytime and windspeed is different at 10 meters height than at the hub height of wind turbines. Therefore, the amount of wind energy that is charged in the smart charging scenarios is lower than it could be in reality. To improve the results, the wind production data should be checked.

The buying process does not contribute an essential functionality to the smart charging module, but does increase the probability of errors. Also, in future cases with higher renewable penetration, the errors created by the buying process become larger, due to the intermittent characteristic of renewable energy. For these reasons, the user of the ABCD model could decide to disable this part of BOX 2. By assuming that electricity can be bought on the moment of charging, the buying process can be neglected. In this case the user has to correct for imperfect buying behaviour of an aggregator to analyse the cost results correctly.

6.3 BOX 3 and smart charging module

The validation of BOX 3 shows some striking results concerning the interaction between smart charging and spot market prices. However, one should take into account the fact that the modelling approach used to create module BOX 3 is a simplification that is not researched extensively. The results of the validation show that the interaction shows interesting dynamics, but in future research the modelling approach of BOX 3 could be assessed more to improve validity and reliability.

Another point of discussion that is concerning validity and reliability is the absence of a sensitivity analyses to assess the smart charging module. In this research time constraints limited the validation of the smart charging module. A sensitivity analyses would strengthen the conclusions that can be drawn with the examination of different scenarios. This will increase the value of the ABCD model including the smart charging module for stakeholders.

6.4 Other points of discussion

Smart charging is also considered to be used as frequency containment reserve (FCR) for the Dutch transmission system operator TenneT. Because FCR only requires a small part of the battery capacity, EV batteries can be used for FCR and smart charging based on price optimisation at the same time. This can be used to optimise the business case for smart charging and makes it more attractive to use smart charging for commercial parties. For further research it would be interesting to assess the possibilities of using FCR in combination with smart charging. The ABCD model is well suitable for this analyses if FCR would be added to the model.

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8 Appendix

8.1 Overview of the ABCD model

The ABCD model simulates the driving and charging behaviour of residents and commuters in the GIS environment of a neighbourhood. People, EVs and charge points are local agents that live in the GIS environment, as is shown in Fig. 22.

Apart from the local agents there are also global agents that are contributing specific features to the ABCD simulations. This created two levels, which is referred to as multi-level modelling in literature (Morvan, 2013) and is inspired by Multi Level Perspective used in Transition Management (Geels, 2011). The global agents are divided into three modules that are presented in **Error! Reference source not found.**.

The buying module is creating EVs with specific properties that can be bought by the residents. It contains the battery manufacturer that is determining the properties of available battery types. The car manufacturer is making EVs of different classes using the batteries from the battery manufacturer. The car dealer can be accessed by the residents and commuters to buy these EVs. Trends in battery prices and drivetrain prices are defined with learning curves.

The driving module is creating driving patterns that determine the driving behaviour of the residents. The data that is used for the driving module is government data on driving behaviour of Dutch citizens. The charging module is creating the charge points in the neighbourhood. A virtual municipality is giving funds to the charge point operator to install charge points in the neighbourhood depending on policy incentives.

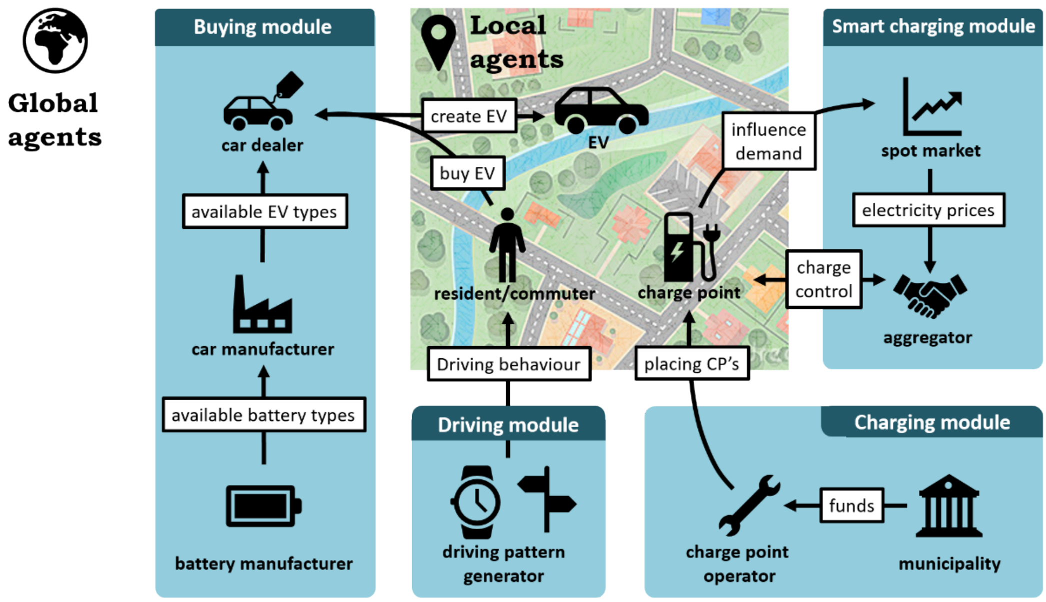

Fig. 24 Overview of the ABCD model. The local agents are living inside the GIS environment of the neighbourhood. The modules with the global agents are contributing specific functionalities to the ABCD model.

Gas and coal price predictions

Coal and gas prices are used to calculate the SRMC of coal and gas generators. To make the spot market supply curve adaptive to analyse future scenarios, coal and gas price predictions until 2035 are included in BOX 1 of the smart charging module. In BOX 1 growth factors are defined for the increase in coal and gas prices over the years. These growth factors are based on ECN predictions of coal and gas prices as is shown in Fig. 25.

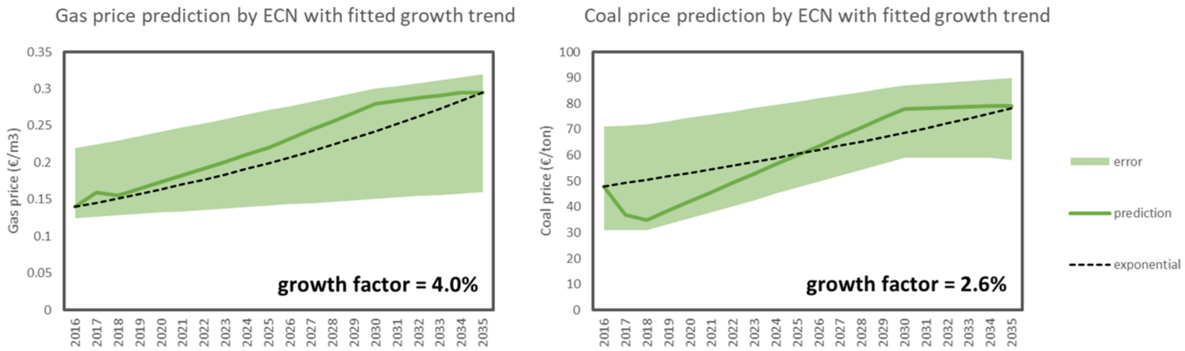

Fig. 25 gas and coal price predictions by ECN from 2016 to 2035 (Schoots, Hekkenberg, and Hammingh 2016). The exponential functions are fitted on the predicted data from ECN and their growth factors are indicated in the graphs.

Carbon tax

The CO_2 price is used to calculate the SRMC in module BOX 1. Similar to the predictions in coal and gas prices, BOX 1 contains a growth factor for CO_2 tax that is used to determine the price for a specific years. This growth factor is based on the ECN data that is plotted with the exponential growth function in Fig. 26.

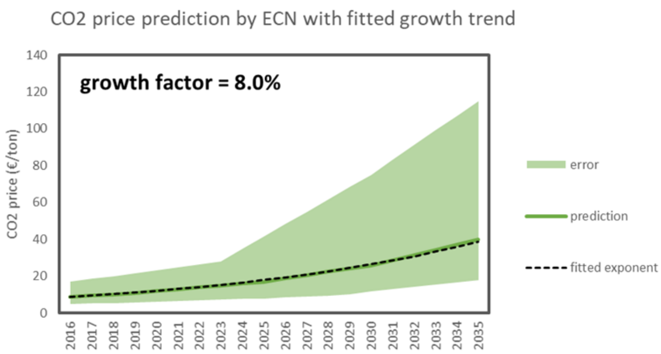

Fig. 26 CO_2 price predictions by ECN from 2016 until 2035 (Schoots, Hekkenberg, and Hammingh 2016). The exponential function is fitted on the predicted data from ECN and the growth factor is indicated in the graph.

Properties of conventional generators

The properties of conventional generators presented in Table 1 are used BOX 1 to calculate the SRMC costs for the different conventional generators. The coal generators that are defined for the supply curve are the old coal generators and the new coal generators. The gas generators that are defined are the old gas turbines, the CHPs, the must-run CHPs and the CCGTs.

Table 1 Properties of conventional generators.

Variable	Value	Unit	Source
COAL			
HHV	32.5	GJ/tonne	(NIST 2017)
CO2 emission factor	2.88	kgCO2/kg	(CO2emissiefactoren.nl 2017)
Efficiency new coal	46%	J electricity/J coal	(Seebregts et al. 2009a)
Efficiency old coal	38%	J electricity/J coal	(Seebregts and Volkers 2005)
GAS			
HHV	31.65	GJ/1000Nm³	(NIST 2017)
CO2 emission factor	1.788	TonneCO2/1000Nm3 gas	(CO2emissiefactoren.nl 2017)
Density natural gas	0.833	tonne gas/1000Nm3 gas	(NIST 2017)
Efficiency old gas	38%	J elec/ J gas	(Seebregts and Volkers 2005)
Efficiency CHP	50%	J elec/ J gas	(Seebregts et al. 2009a)
Efficiency CCGT	58%	J elec/ J gas	(Seebregts et al. 2009a)
Percentage CHP must-run	20%		(Seebregts et al. 2009a)

Properties of renewable generators

The SRMC of renewable and nuclear generation is assumed to be constant, because their SRMC are hard to determine and are mostly not influencing the spot market prices. The values for onshore, offshore, PV and nuclear generation are presented in Table 2.

Table 2 SRMC of onshore, offshore, PV and nuclear generation.

Variable	Value	Unit	Source
Onshore	2.0	€/MWh	(Seebregts et al. 2009a)
Offshore	2.5	€/MWh	(Seebregts et al. 2009a)
PV	6.0	€/MWh	(Seebregts et al. 2009a)
Nuclear	14	€/MWh	(Seebregts et al. 2009a)

8.3 Installed capacities

The installed capacities of different generators are presented in Table 3. The rows with that are market with bold fond is the data that is gathered from ECN. The numbers in between the bold rows is interpolated.

Table 3 Installed capacities for different generators in The Netherlands from 2016 estimated until 2035. The rows with bold shading is the data that is used from ECN (Schoots et al., 2016; Seebregts et al., 2009b). This data for renewable capacity is used for both merit-orders of BOX 1. The conventional capacity is used to construct the supply curve for the ECN NL merit-order.

Year	Onshore	Offshore	PV	Nuclear	Coal new	CCGT	CHP	Old gas	Conventional	Renewable	TOTAL
2016	**3500**	**500**	**1000**	**450**	**4500**	**5500**	**12500**	**6000**	**28950**	**5000**	**33950**
2017	4000	1000	1500	450	4500	5500	12500	6000	28950	6500	35450
2018	4500	1500	2000	450	4500	5500	12500	6000	28950	8000	36950
2019	5000	2000	2500	450	4500	5500	12500	6000	28950	9500	38450
2020	**5500**	**2500**	**3000**	**450**	**4500**	**5500**	**12500**	**6000**	**28950**	**11000**	**39950**
2021	6000	3000	3500	450	4500	5500	10000	6000	26450	12500	38950
2022	6500	3500	4000	450	4500	5500	10000	6000	26450	14000	40450
2023	**7000**	**4000**	**5000**	**450**	**3300**	**5500**	**10000**	**6000**	**25250**	**16000**	**41250**
2024	7000	4500	6000	450	3300	5500	7500	6000	22750	17500	40250
2025	7000	5000	7500	450	3300	5500	7500	6000	22750	19500	42250
2026	7000	5500	9000	450	3300	3000	7500	6000	20250	21500	41750
2027	7000	6000	10500	450	3300	3000	7500	6000	20250	23500	43750
2028	7000	6500	12000	450	3300	3000	7500	6000	20250	25500	45750
2029	7000	7000	13500	450	3300	3000	7500	6000	20250	27500	47750
2030	**7000**	**7500**	**15000**	**450**	**3300**	**3000**	**7500**	**6000**	**20250**	**29500**	**49750**
2031	7000	8000	16000	0	0	3000	7500	6000	16500	31000	47500
2032	7000	8500	17000	0	0	3000	7500	6000	16500	32500	49000
2033	7000	9000	18000	0	0	3000	7500	6000	16500	34000	50500
2034	7000	9500	19000	0	0	3000	7500	6000	16500	35500	52000
2035	**7000**	**10000**	**20000**	**0**	**0**	**3000**	**7500**	**6000**	**16500**	**37000**	**53500**

8.4 Spot market demand

Hourly average load data

The demand on the spot market is determined by the sum of the bids in kWh for a specific hour. The demand on the EPEX day-ahead market is following the same trend as the national electricity demand of The Netherlands. The reason for this is that the EPEX day-ahead market is the most prominent spot market in the Netherlands for bidders to balance their electricity portfolio (Drs.ir. M.P.G. Sewalt, 2003).

The national demand of the Netherlands follows a stable trend with a rising demand in the morning, stable load during midday and a peak in the evening as is indicated in Fig. 27. The morning peak starts when people wake up and go to work. The evening peak starts when people arrive home and start to use more home appliances. The trend is stable during the week, but is different for Saturdays and Sundays. During the weekends the morning peak starts later because people start their activities later and the total demand is lower because most organisations are non-active during the weekend. Because the week demand and the weekend demand are quite well defined they can be used to predict the electricity demand on the EPEX day-ahead market.

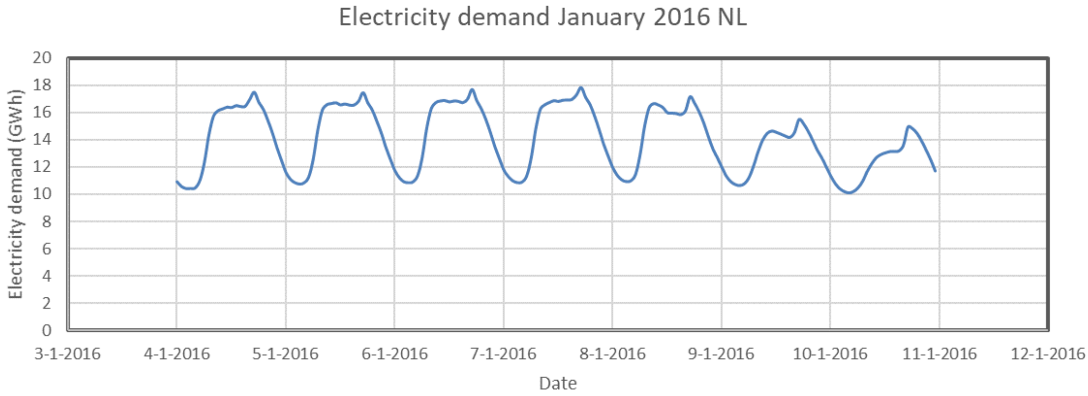

Fig. 27 Electricity demand in The Netherlands in the second week of January 2016 (ENTSO-E, 2016). The demand follows a specific trend throughout the day. In the morning the demand increases to a stable level during midday. In the evening there is a peak when people come home from work and the use of home appliances goes up. In the weekends (10th and 11th of January) the demand is lower and the morning peak starts later.

Baseline demand increase due to electrification

Electrification is increasing the demand on spot market in The Netherlands. To make BOX 1 more adaptive to this changing demand a baseline demand increase growth factor is defined. This growth factor can be used to calculate the electricity demand for a specific year. The growth factor is based on ECN research which is also presented in Fig. 28 *(Schoots et al., 2016)*.

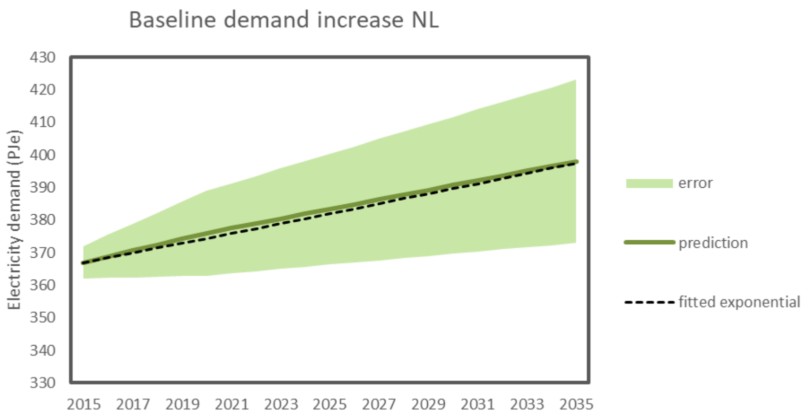

Fig. 28 Baseline demand increase of NL national demand based on ECN studies in the growth of Dutch electricity demand (Schoots et al., 2016). *A growth function (power function) is fitted on the predicted data points using the Excel fitting option. In the equation the t is the time in years and the D is the Demand in PJ (electric).*

8.5 GAMA code for spot market

```
/**
* Name: ABCD_spotmarket
* Author: Michiel
* Description: Describe here the model and its experiments
* Tags: Tag1, Tag2, TagN
*/

model ABCD_spotmarket

import "ABCD_SmartCharging.gaml"

global
{
    bool weekday;
    string day_of_week;
    string path_to_result_folder <- "../results/BOX1_results/2025_fitted/";

    // ALL AVAILABLE DEMAND FILES
    string path_to_demand_file <- "../includes/Electricity_market/average_demand_curves_2016.csv";
//  string path_to_demand_file <- "../includes/Electricity_market/NL_demand_2016.csv";

    // AVAILABLE MERIT-ORDERS
//  string NL_merit_order <- "ECN merit-order"; // use NL merit order if true, else use linear scaling of demand to determine prices.
    string NL_merit_order <- "customised merit-order"; // use NL merit order if true, else use linear scaling of demand to determine prices.

    // DASH BOARD
    bool influence_of_charging_on_spotmarket_demand <- false; // Setting reflex update national demand curves ON or OFF
    float CO2_price_growth_factor <- 1.08; // Exponential growth factor of CO2 price (%)
    float gas_price_growth <- 1.04; // exponential growth factor of gas price (%)
    float coal_price_growth <- 1.026; // exponential growth factor of coal price (%)
    float SRMC_onshore <- 2.0; // Source: Brandstofmix elektriciteit 2020 inventarisatie, ECN
    float SRMC_offshore <- 2.5; // Source: Brandstofmix elektriciteit 2020 inventarisatie, ECN
    float SRMC_PV <- 6.0; // Source: Brandstofmix elektriciteit 2020 inventarisatie, ECN
    float SRMC_nuclear <- 14.0; // Source: Brandstofmix elektriciteit 2020 inventarisatie, ECN
    float percentage_must_run <- 0.2; // Percentage of CHP plants must run. Source: Brandstofmix elektriciteit 2020 inventarisatie, ECN
    float baseline_car_increase_NL <- 1.0177; // percentage increase of cars in NL. Based on fitting of increase from 1990 till 2017
    float baseline_demand_increase <- 1.004; // the baseline electricity demand increase NL is determined at 0,4% per year. Source: ECN, national energy outlook, 2015
    bool baseline_demand_increase_on <- false;
    float demand_scaling_factor <- total_amount_cars_in_NL / 200;

    // Specific times for spotmarket
    int market_opening_minute <- 0;
    int market_closing_hour <- 0;
    int market_closing_minute <- 0;

    // Demand variables (demand curves are depending on workday or holiday)
    file demand_file; // file containing demand
    matrix demand_matrix; // matrix containing demand arrays
    list<float> workday_demand_curve; // list with the current workday demand curve
    list<float> holiday_demand_curve; // list with the current holiday demand curve
    list<float> workday_demand_curve_2016; // list with the current workday demand curve
    list<float> holiday_demand_curve_2016; // list with the current holiday demand curve
    list<float> demand_curve_2016;
    int days_past;

    // SRMC variables
    // CO2 prices
    float current_CO2_price <- 9.0; // Current price of CO2 emmissions (€/tonneCO2)

    // Gas
    float current_gas_price <- 0.14; // €/Nm3 in 2016 (this can be updated for future prices)
    float HHV_gas <- 31.65; // MJ/m3. Source: Groningen gas HHV wikipedia
    float emission_factor_gas <- 1.788; // kgCO2/Nm3. Source: CO2emissiefactoren.nl
    float efficiency_gas_old <- 0.38; // Efficiency of the oldest gas plants (J elec/J gas) source: Vragen over nieuwe kolencentrales in Nederland Achtergrond en inleiding
    float efficiency_CHP <- 0.5; // Efficiency of the oldest gas plants (J elec/J gas) source: Vragen over nieuwe kolencentrales in Nederland Achtergrond en inleiding
    float efficiency_CCGT <- 0.58; // Efficiency of the newest gas plants (J elec/J gas) source: Vragen over nieuwe kolencentrales in Nederland Achtergrond en inleiding
    float market_power_bonus <- 2.0; // Multiplication factor for the electricity price of the most expensive generator in the merit-order because of market power

    // Coal
    float current_coal_price <- 48.0; // €/tonne coal. in 2016 (this can be updated for future prices)
    float HHV_coal <- 32.5; // MJ/kg. Source: anthracite HHV wikipedia
    float emission_factor_coal <- 2.88; // kgCO2/kg. Source: co2emissiefactoren.nl
    float efficiency_coal_old <- 0.38; // Efficiency of the oldest coal plants (J elec/J coal) source: Vragen over nieuwe kolencentrales in Nederland Achtergrond en inleiding
    float efficiency_coal_new <- 0.46; // Efficiency of the newest coal plants (J elec/J coal) source: Vragen over nieuwe kolencentrales in Nederland Achtergrond en inleiding

    // NOTE: csv_file action does not include the first row in the CSV file!!!

    // importing wind and sun data from KNMI (normalised)
    file KNMI_2016_file <- csv_file("../includes/Electricity_market/KNMI_wind_sun_2016.csv", ",");
    matrix KNMI_2016_matrix <- matrix(KNMI_2016_file);
    list<float> wind_data_2016 <- KNMI_2016_matrix column_at 0;
    list<float> sun_data_2016 <- KNMI_2016_matrix column_at 1;

    // importing supply data from ECN from 2016 until 2035 (MW)
    file supply_file <- csv_file("../includes/Electricity_market/supply_data_2016-2035.csv", ",");
    matrix supply_matrix <- matrix(supply_file);
    list<int> years_list <- supply_matrix column_at 0;
    list<float> onshore_supply_list <- supply_matrix column_at 1;
    list<float> offshore_supply_list <- supply_matrix column_at 2;
    list<float> PV_supply_list <- supply_matrix column_at 3;
    list<float> nuclear_supply_list <- supply_matrix column_at 4;
    list<float> new_coal_supply_list <- supply_matrix column_at 5;
    list<float> CCGT_supply_list <- supply_matrix column_at 6;
    list<float> CHP_supply_list <- supply_matrix column_at 7;
    list<float> old_gas_supply_list <- supply_matrix column_at 8;
```

```
reflex supply_update when: current_date.month = 12 and current_date.day = 31 and current_date.hour = 23 and current_date.minute = 0
{
// updating SRMC and supply lists every year on the 1st of january, 00:15

// SRMC attributes
    fuel_cost_coal_new <- fuel_cost_coal_new * coal_price_growth; // Fuel cost in €/MWh coal (high efficiency coal)
    fuel_cost_coal_old <- fuel_cost_coal_old * coal_price_growth; // Fuel cost in €/MWh coal (low efficiency coal)
    fuel_cost_CCGT <- fuel_cost_CCGT * gas_price_growth; // Fuel cost in €/MWh CCGT (high efficiency gas)
    fuel_cost_CHP <- fuel_cost_CHP * gas_price_growth; // Fuel cost in €/MWh CHP (CHP efficiency gas)
    fuel_cost_gas_old <- fuel_cost_gas_old * gas_price_growth; // Fuel cost in €/MWh gas (low efficiency gas)

    CO2_cost_coal_new <- CO2_cost_coal_new * CO2_price_growth_factor; // CO2 cost in €/MWh coal (high efficiency coal)
    CO2_cost_coal_old <- CO2_cost_coal_old * CO2_price_growth_factor; // CO2 cost in €/MWh coal (low efficiency coal)
    CO2_cost_CCGT <- CO2_cost_CCGT * CO2_price_growth_factor; // CO2 cost in €/MWh CCGT (high efficiency gas)
    CO2_cost_CHP <- CO2_cost_CHP * CO2_price_growth_factor; // CO2 cost in €/MWh CHP (CHP efficiency gas)
    CO2_cost_gas_old <- CO2_cost_gas_old * CO2_price_growth_factor; // CO2 cost in €/MWh gas (low efficiency gas)

    SRMC_coal_new <- fuel_cost_coal_new + CO2_cost_coal_new;
    SRMC_coal_old <- fuel_cost_coal_old + CO2_cost_coal_old;
    SRMC_CCGT <- fuel_cost_CCGT + CO2_cost_CCGT;
    SRMC_CHP <- fuel_cost_CHP + CO2_cost_CHP;
    SRMC_gas_old <- (fuel_cost_gas_old + CO2_cost_gas_old) * market_power_bonus;

    // Supply lists
    installed_cap_onshore <- onshore_supply_list[current_date.year - years_list[0]];
    installed_cap_offshore <- offshore_supply_list[current_date.year - years_list[0]];
    installed_cap_PV <- PV_supply_list[current_date.year - years_list[0]];
    installed_cap_nuclear <- nuclear_supply_list[current_date.year - years_list[0]];
    installed_cap_new_coal <- new_coal_supply_list[current_date.year - years_list[0]];
    installed_cap_CCGT <- CCGT_supply_list[current_date.year - years_list[0]];
    installed_cap_CHP <- CHP_supply_list[current_date.year - years_list[0]];
    installed_cap_old_gas <- old_gas_supply_list[current_date.year - years_list[0]];
}

reflex market_opening when: current_date.hour = 0 and current_date.minute = 0{
// Opening of market on 00:00 every day. Update of supply, demand and price.

    if influence_of_charging_on_spotmarket_demand = true
    {
        int i <- 0;
        loop times: 24
        {
            demand_shift[i] <- demand_scaling_factor * average_kWh_usage_for_charging_workday[i] / 1000;
            i <- i + 1;
        }
    }

    do price_calculation;

    days_past <- days_past + 1;
}

action price_calculation
{
// Set random index for wind and PV supply
    rnd_index <- rnd(360) * 24;

    // save day_ahead_prices for the next day in todays_elec_prices
    todays_elec_prices <- copy_between(day_ahead_prices, 0, 24);

    // loop over all hours in a day
    int i <- 0;
    loop times: 24
    {
        if path_to_demand_file = "../includes/Electricity_market/NL_demand_2016.csv"
        {
            onshore_supply[i] <- wind_data_2016[days_past * 24 + i] * installed_cap_onshore;
            offshore_supply[i] <- wind_data_2016[days_past * 24 + i] * installed_cap_offshore;
        } else
        {
            onshore_supply[i] <- wind_data_2016[rnd_index + i] * installed_cap_onshore;

            offshore_supply[i] <- wind_data_2016[rnd_index + i] * installed_cap_offshore;
        }
        if path_to_demand_file = "../includes/Electricity_market/NL_demand_2016.csv"
        {
            PV_supply[i] <- sun_data_2016[days_past * 24 + i] * installed_cap_PV;
        } else
        {
            PV_supply[i] <- sun_data_2016[rnd_index + i] * installed_cap_PV;
        }

        nuclear_supply <- installed_cap_nuclear;
        new_coal_supply <- installed_cap_new_coal;
        CCGT_supply <- installed_cap_CCGT;
        CHP_supply <- installed_cap_CHP;
        old_gas_supply <- installed_cap_old_gas * 2;

        Onshore <- onshore_supply[i];
        Offshore <- Onshore + offshore_supply[i];
        PV <- Offshore + PV_supply[i];
        Nuc <- PV + nuclear_supply;
        NEWc <- Nuc + new_coal_supply;
        MustRun <- NEWc + percentage_must_run * CHP_supply;
        CCGT <- MustRun + CCGT_supply;
        CHP <- CCGT + (1 - percentage_must_run) * CHP_supply;
        OLDg <- CHP + old_gas_supply;

        if path_to_demand_file = "../includes/Electricity_market/NL_demand_2016.csv"
        {
            if influence_of_charging_on_spotmarket_demand = true
            {
                demand[i] <- demand_curve_2016[days_past * 24 + i] + demand_shift[i];
            } else
            {
                demand[i] <- demand_curve_2016[days_past * 24 + i];
            }
        } else
        {
            if influence_of_charging_on_spotmarket_demand = true
            {
```

```
                // Demand during workdays
                if (weekday = true and current_date.day_of_week != 5) or current_date.day_of_week = 7
                {
                    demand[i] <- workday_demand_curve[i] + demand_shift[i];
                }
                // Demand during holidays
                else
                {
                    demand[i] <- holiday_demand_curve[i] + demand_shift[i];
                }
            } else
            {
                // Demand during workdays
                if (weekday = true and current_date.day_of_week != 5) or current_date.day_of_week = 7
                {
                    demand[i] <- workday_demand_curve[i];
                }
                // Demand during holidays
                else
                {
                    demand[i] <- holiday_demand_curve[i];
                }
            }
        }

        // WHEN MERIT-ORDER = ECN
        if NL_merit_order = "ECN merit-order"
        {
        // Calculating price list (24 hours)
        if (demand[i] < Onshore)
        {
            day_ahead_prices[i] <- SRMC_onshore;
        } else if (demand[i] >= Onshore and demand[i] < Offshore)
        {
            day_ahead_prices[i] <- SRMC_offshore;
        } else if (demand[i] >= Offshore and demand[i] < PV)
        {
            day_ahead_prices[i] <- SRMC_PV;
        } else if (demand[i] >= PV and demand[i] < Nuc)
        {
            day_ahead_prices[i] <- SRMC_nuclear;
        } else if (demand[i] >= Nuc and demand[i] < NEWc)
        {
            day_ahead_prices[i] <- SRMC_coal_new;
        } else if (demand[i] >= NEWc and demand[i] < MustRun)
        {
            day_ahead_prices[i] <- SRMC_CHP * 2 / 3;
        } else if (demand[i] >= MustRun and demand[i] < CCGT)
        {
            slope <- (SRMC_CCGT - SRMC_CHP * 2 / 3) / CCGT_supply;
            intersect_y_axis <- SRMC_CCGT - slope * (CCGT);
            day_ahead_prices[i] <- slope * demand[i] + intersect_y_axis;
        } else if (demand[i] >= CCGT and demand[i] < CHP)
        {
            slope <- (SRMC_CHP - SRMC_CCGT) / CHP_supply;
            intersect_y_axis <- SRMC_CHP - slope * (CHP);
            day_ahead_prices[i] <- slope * demand[i] + intersect_y_axis;
        } else
        {
            slope <- (SRMC_gas_old - SRMC_CHP) / old_gas_supply;
            intersect_y_axis <- SRMC_gas_old - slope * (OLDg);
            day_ahead_prices[i] <- slope * demand[i] + intersect_y_axis;
        }
        } // WHEN MERIT ORDER = CUSTOMISED
        else if NL_merit_order = "customised merit-order"
        {
        if demand[i] < (NEWc)
        {
            slope <- 9 / (NEWc);
            intersect_y_axis <- 0.0;
            day_ahead_prices[i] <- slope * demand[i] + intersect_y_axis;
        }else
        {
            day_ahead_prices[i] <- exp(0.0008*(demand[i]-(CCGT+PV)))+46.3/(CHP-NEWc)*(demand[i]-PV)-11;
        }
        }

        i <- i + 1;
    }
}
```

8.6 GAMA code for connection with charge points

```
model ABCDcharging

import "ABCD_build.gaml"

species home_CP parent: CP
{

    action home_smart_charging
    {
        if car_charging.charge_trigger = false and car_charging.owner.evening_trip_depart_time = nil
        {
            ask my_aggregator
            {
                my_EV <- myself.car_charging;
                stop_charge_hr <- my_EV.owner.dayahead_start_work_hr;
                stop_charge_m <- my_EV.owner.dayahead_start_work_m;
                do make_charge_schedule;
            }

            schedule <- car_charging.charge_schedule;
            car_charging.charge_trigger <- true;
        }

        if car_charging.charge_trigger = true
        {
            car_charging.kW_sc_home <- schedule[current_date.hour];
            if schedule[current_date.hour] != 0.0
            {
                car_charging.kWh_charged <- car_charging.kWh_charged + schedule[current_date.hour] * step / (60 * 60);
                car_charging.kWh_in_battery <- car_charging.kWh_in_battery + schedule[current_date.hour] * step / (60 * 60);
                cumm_kWh_supplied <- cumm_kWh_supplied + schedule[current_date.hour] * step / (60 * 60);
            }

            if car_charging.kWh_in_battery = car_charging.battery_capacity
            {
                in_use <- false;
                car_charging.current_activity <- "Finished_charging_at_home_CP";
                car_charging.kW_sc_home <- 0.0;
                car_charging.charge_trigger <- false;
                car_charging <- nil;
            }

        }

    }
}

species work_charger parent: CP
{
    action work_smart_charging
    {
        if car_charging.charge_trigger = false
        {
            ask my_aggregator
            {
                my_EV <- myself.car_charging;
                stop_charge_hr <- my_EV.owner2.todays_end_work_hr;
                stop_charge_m <- my_EV.owner2.todays_end_work_m;
                do make_charge_schedule;
            }

            schedule <- car_charging.charge_schedule;
            car_charging.charge_trigger <- true;
        }

        if car_charging.charge_trigger = true
        {
            car_charging.kW_sc_work <- schedule[current_date.hour];
            if schedule[current_date.hour] != 0.0
            {
                car_charging.kWh_charged <- car_charging.kWh_charged + schedule[current_date.hour] * step / (60 * 60);
                car_charging.kWh_in_battery <- car_charging.kWh_in_battery + schedule[current_date.hour] * step / (60 * 60);
                cumm_kWh_supplied <- cumm_kWh_supplied + schedule[current_date.hour] * step / (60 * 60);
            }

            if car_charging.kWh_in_battery = car_charging.battery_capacity
            {
                in_use <- false;
                car_charging.current_activity <- "Finished_charging_at_home_CP";
                car_charging.kW_sc_work <- 0.0;
                car_charging.charge_trigger <- false;
                car_charging <- nil;
            }

        }

    }
```

```
    action work_smart_charging
    {
        if car_charging.charge_trigger = false
        {
            ask my_aggregator
            {
                my_EV <- myself.car_charging;
                stop_charge_hr <- my_EV.owner2.todays_end_work_hr;
                stop_charge_m <- my_EV.owner2.todays_end_work_m;
                do make_charge_schedule;
            }

            schedule <- car_charging.charge_schedule;
            car_charging.charge_trigger <- true;
        }

        if car_charging.charge_trigger = true
        {
            car_charging.kW_sc_work <- schedule[current_date.hour];
            if schedule[current_date.hour] != 0.0
            {
                car_charging.kWh_charged <- car_charging.kWh_charged + schedule[current_date.hour] * step / (60 * 60);
                car_charging.kWh_in_battery <- car_charging.kWh_in_battery + schedule[current_date.hour] * step / (60 * 60);
                cumm_kWh_supplied <- cumm_kWh_supplied + schedule[current_date.hour] * step / (60 * 60);
            }

            if car_charging.kWh_in_battery = car_charging.battery_capacity
            {
                in_use <- false;
                car_charging.current_activity <- "Finished_charging_at_home_CP";
                car_charging.kW_sc_work <- 0.0;
                car_charging.charge_trigger <- false;
                car_charging <- nil;
            }

        }

    }
}

species public_CP parent: CP
{
    action public_smart_charging
    {
        if car_charging.current_activity = "charging_at_public_charger_during_work_commuter"
        {
            ask my_aggregator
            {
                my_EV <- myself.car_charging;
                stop_charge_hr <- my_EV.owner2.todays_end_work_hr;
                stop_charge_m <- my_EV.owner2.todays_end_work_m;
                do make_charge_schedule;
            }

            schedule <- car_charging.charge_schedule;
            car_charging.charge_trigger <- true;
        } else if car_charging.current_activity = "charging_near_home_public"
        {
            ask my_aggregator
            {
                my_EV <- myself.car_charging;
                stop_charge_hr <- my_EV.owner.dayahead_start_work_hr;
                stop_charge_m <- my_EV.owner.dayahead_start_work_m;
                do make_charge_schedule;
            }

            schedule <- car_charging.charge_schedule;
            car_charging.charge_trigger <- true;
        } else if car_charging.charge_trigger = true and length(schedule) = 0
        {
            write "NO SCHEDULE!!!";
            car_charging.charge_trigger <- false;
        } else if car_charging.charge_trigger = true
        {
            if car_charging.current_activity = "charging_at_public_charger_during_work_commuter"
            {
                car_charging.kW_sc_public_near_work <- schedule[current_date.hour];
            } else if car_charging.current_activity = "charging_near_home_public"
            {
                car_charging.kW_sc_public_near_home <- schedule[current_date.hour];
            }

            if schedule[current_date.hour] != 0.0
            {
                car_charging.kWh_charged <- car_charging.kWh_charged + schedule[current_date.hour] * step / (60 * 60);
                car_charging.kWh_in_battery <- car_charging.kWh_in_battery + schedule[current_date.hour] * step / (60 * 60);
                cumm_kWh_supplied <- schedule[current_date.hour] * step / (60 * 60) + cumm_kWh_supplied;
            }

            if car_charging.kWh_in_battery = car_charging.battery_capacity
            {
                in_use <- false;
                car_charging.current_activity <- "Finished_charging_at_public_CP";
                car_charging.kW_sc_public_near_work <- 0.0;
                car_charging.kW_sc_public_near_home <- 0.0;
                car_charging.charge_trigger <- false;
                car_charging <- nil;
            }

        } else if car_charging.current_activity = "charging_near_home_public" and car_charging.charge_trigger = false and car
        {
        // EV will not charge because he will leave for an evening trip
        } else
        {
            write "ERROR in public_smart_charging: charge session not defined for some reason, " + car_charging.name
        }

    }

```

```
model ABCD_SmartCharging

import "ABCD_spotmarket.gaml"
import "ABCD_cars.gaml"

global{

    // DASHBOARD
    float weight_kWh_usage <- 10 * (1#hour / step);                    // the weight for the calculation on average kWh usage for charging in the neighborhood
    // innitialise smart_aggregator
    init
    {
        create smart_aggregator number: nb_smart_aggregator_init;
        my_aggregator <- one_of(smart_aggregator);
    }

}

species smart_aggregator
{
    reflex calculate_kW_charged
    {
    // calculate the total amount of kW that is charged at every time step.
        kW_sc_home <- sum(EVfromresidents collect each.kW_sc_home);
        kW_sc_work <- sum(EVfromcommuters collect each.kW_sc_work);
        kW_sc_public_near_home <- sum(EVfromresidents collect each.kW_sc_public_near_home);
        kW_sc_public_near_work <- sum(EVfromcommuters collect each.kW_sc_public_near_work);
        kW_usage_smart_charging <- kW_sc_home + kW_sc_work + kW_sc_public_near_home + kW_sc_public_near_work;
        kW_usage_normal_charging <- sum(EVfromresidents collect each.kW_currently_charging) + sum(EVfromcommuters collect each.kW_currently_charging);
        kW_usage_charging <- kW_usage_smart_charging + kW_usage_normal_charging;

        // Calculate kWh_usage during this day
        if current_date.minute = 0
        {
            kWh_charged[current_date.hour] <- kW_usage_charging * (step / 1#hour);
        } else
        {
            kWh_charged[current_date.hour] <- kWh_charged[current_date.hour] + kW_usage_charging * (step / 1#hour);
        }

        // Use the kW_usage to update the average kWh_usage in the neighborhood. This list can be used by the spot_market to recalculate the demand.

        // For workdays
        if weekday{
            if days_past < weight_kWh_usage
            {
                average_kWh_usage_for_charging_workday[current_date.hour] <-
                (days_past * average_kWh_usage_for_charging_workday[current_date.hour] + kW_usage_charging) / (days_past + 1);
            }else
            {
                average_kWh_usage_for_charging_workday[current_date.hour] <-
                (weight_kWh_usage * average_kWh_usage_for_charging_workday[current_date.hour] + kW_usage_charging) / (weight_kWh_usage + 1);
            }
        }

    }

    reflex calculate_charging_costs when: current_date.hour = 0 and current_date.minute = 0
    {
        do calculate_charging_costs;
    }

    action calculate_charging_costs
    {
        charging_costs <- 0.0;

        loop i over: hours_in_a_day_int
        {
            charging_costs <- charging_costs + kWh_charged[i] * todays_elec_prices[i];
        }
        if sum(kWh_charged) != 0.0

        {
            charging_costs <- charging_costs / sum(kWh_charged);
        }


    }

    action make_charge_schedule
    {
    // find the owner of the EV and store in EV_owner
        if my_EV.EV_from_a_resident = true
        {
            EV_owner <- my_EV.owner;
        } else
        {
            EV_owner <- my_EV.owner2;
        }
        // Setting charge_schedule to default
        charge_schedule <- list_with(24, 0.0);

        // define the start times of charge session
        start_charge_hr <- current_date.hour;
```

```
        start_charge_m <- current_date.minute;

        // define the charge needs of my_EV for the night charge
        charge_need <- my_EV.battery_capacity - my_EV.kWh_in_battery; // current state of battery;

        // WEEKDAY
        if weekday or (current_date.day_of_week = 7 and current_date.hour > 12)
        {
            if my_EV.current_activity = "charging_near_home_public" or my_EV.current_activity = "charging_at_home"
            {
                stop_charge_hr <- EV_owner.dayahead_start_work_hr;
                stop_charge_m <- EV_owner.dayahead_start_work_m;

                // prepare the optimisation arrays for smart charge optimisation
                price_array <- copy_between(todays_elec_prices, start_charge_hr, 23);
                add copy_between(day_ahead_prices, 0, stop_charge_hr) all: true to: price_array;
            } else if my_EV.current_activity = "charging_at_public_charger_during_work_commuter" or my_EV.current_activity = "charging_at_work"
            {
                stop_charge_hr <- EV_owner.todays_end_work_hr;
                stop_charge_m <- EV_owner.todays_end_work_m;

                // prepare the optimisation arrays for smart charge optimisation
                price_array <- copy_between(todays_elec_prices, start_charge_hr, stop_charge_hr);
            } else
            {
                write "ERROR: no optimisation array defined for " + my_EV + ". driver type: " + EV_owner.driver_type + ". current activity: " +
            }
            // Determine optimal charge schedule
            do smart_charge_optimisation;
            my_EV.charge_schedule <- charge_schedule;

        }

    }

    action smart_charge_optimisation
    {
        need_more_kWh <- true;
        nb_iterations <- 1;
        loop while: need_more_kWh
        {

            charge_index <- index_of(price_array, min(price_array));

            // Perform smart charging optimisation
            do determine_kWh_charged_in_charge_block;

            // Check if more kWh needs to be charged
            if charge_need = 0.0 or nb_iterations = length(optimisation_array)
            {
                need_more_kWh <- false;
            } // Update optimisation array to avoid dubbel charging
            price_array[charge_index] <- max(price_array)+1;

            // adjust number of iterations
            nb_iterations <- nb_iterations + 1;
        }
    }

    action determine_kWh_charged_in_charge_block
    {
        if my_EV.current_activity = "charging_near_home_public" or my_EV.current_activity = "charging_at_home"
        {
            if charge_index <= (23 - start_charge_hr)
            {
                charge_hour <- charge_index + start_charge_hr;
            } else
            {
                charge_hour <- charge_index + start_charge_hr - 24;
            }

        } else
        {
            charge_hour <- charge_index + start_charge_hr;
        }
        // check how many minutes the car is plugged in during the cheapest hour
        if charge_hour = start_charge_hr
        {
            full_charge_block <- (1 - start_charge_m / 60) * charging_speed;
        } else if charge_hour = stop_charge_hr
        {
            full_charge_block <- stop_charge_m / 60 * charging_speed;
        } else
        {
            full_charge_block <- charging_speed;
        }
        // check if the charge need is satisfied after current iteration
        if charge_need > full_charge_block
        {
            charge_schedule[charge_hour] <- charge_schedule[charge_hour] + full_charge_block;
            // adjust charge need
            charge_need <- charge_need - full_charge_block;
        } else
        {
            charge_schedule[charge_hour] <- charge_schedule[charge_hour] + charge_need;
            // adjust charge need
            charge_need <- 0.0;
        }

    }
}
```