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**Author(s):** Jäntti, Maarit; Jäntti, Anssi; Shafie-khah, Miadreza

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# Towards customer-centric power grid: Residential EV charging simulator for smart homes

Maarit Jäntti, Anssi Jäntti, Miadreza Shafie-khah\*

*School of Technology and Innovations, University of Vaasa, 65200 Vaasa, Finland*

## Abstract

The role of the end-users in the energy markets is changing from passive consumers to active prosumers, hence new solutions in the energy markets need to be designed in a user-centric way. This chapter focuses on transition towards decentralized power grids where the role of consumers in making decision is significant. On this basis, a smart home demand response simulator is presented. The smart home includes electric vehicle, and EV charging simulator program is developed for the economics of charging an electric car under different conditions based on the habits of the user. The model contains several profiles related to power economics, and the implications of these can be evaluated under the specified conditions.

## Acronyms

CP – Convex Programming – Mathematical optimization technique which can be utilized if the problem can be presented as certain types of convex functions.

BEV – Battery Electric Vehicle – Commonly shortened just to EV.

DLP – Dynamic Load Priority – A concept by which the priority of various loads is being dynamically adjusted during a demand response event.

DR – Demand Response – Adjustment of customers' electricity demand as a response to the changing conditions of the electrical network.

DRM – Demand Response Management – A process for managing devices in order to enable the demand response functionality.

EV – Electric Vehicle – A machine used for transportation, uses one or more engines and electricity for propulsion.

FPCTTH – Fiber Power Cable To The Home – A type of cabling which combines the delivery of electrical power and fiber optic connection for residential buildings.

PSO – Particle Swarm Optimization – An iterative optimization technique where candidate solutions (“particles”) move around the search-space like certain birds or fish.

SG – Smart Grid – Electrical grid which includes for example various smart components and renewable resources.

SH – Smart Home – A residential building with varying level of home automation and connected appliances.

SHIM – Supervisor Control and Data Acquisition House Intelligent Management – A smart home simulation system developed at the Polytechnic of Porto.

V2G – Vehicle To Grid – Transferring power from EVs to the electric grid, using the EVs as battery storage for the grid.

# 1 Introduction

Renewable energy sources, the Internet of Things and electrification are acknowledged development trends that are affecting energy markets globally. These drivers will most probably increase the need for demand and storage flexibility. The role of the end-users in the energy markets is changing from passive consumers to active prosumers and therefore the new solutions in the energy markets need to be designed in a user-centric way. The motives, incentives, requirements, and criteria of consumers need to take into considerations and furthermore, how consumers could support the business goals of the different energy domain actors (Immonen, Kiljander, & Aro, 2019).

In this chapter, firstly, a literature review will be presented about demand response, the role of governments and regulators including incentives, benefits to the electricity consumers to participate in the electricity market and also the regulatory barriers. Afterward, a smart home demand response simulation including electric vehicles will be presented. An EV charging simulator program has been developed for the economics of charging an electric car under different conditions. The program is used to simulate the depleting and charging of an electric car based on the habits of its user. The program contains several different profiles related to power economics, and the implications of these can be evaluated under the specified conditions. The program tries to automatically load the Nord Pool spot price database and it takes as inputs several parameters regarding the car and its usage extracted from real data of daily driving. The battery size and charger capacity are taken from a standard Nissan Leaf **equipped** with the basic onboard AC charger intended for home use from a normal 16A wall outlet. The work focuses on transition towards decentralized power grids where the role of consumers in making decision is significant.

## 2 Literature review

### 2.1 Demand response

One solution to make the power grid more secure, efficient, and cleaner is to make electricity consumption more flexible. Balancing electricity consumption to reduce peaks in demand or take advantage of renewable energy sources is described as demand side flexibility. (The European Consumer Organisation, 2018)

From consumer's viewpoint demand flexibility or demand response (DR) means that the electricity consumers shift the timing of their electricity consumption behavior when required, for example washing laundry or heating water at different times than usual (Immonen, Kiljander, & Aro, 2019) or smart charging strategies that shift the time of day when EVs are charging from the grid (International Energy Agency, 2020). Figure 1 shows different layers of demand response implementations.

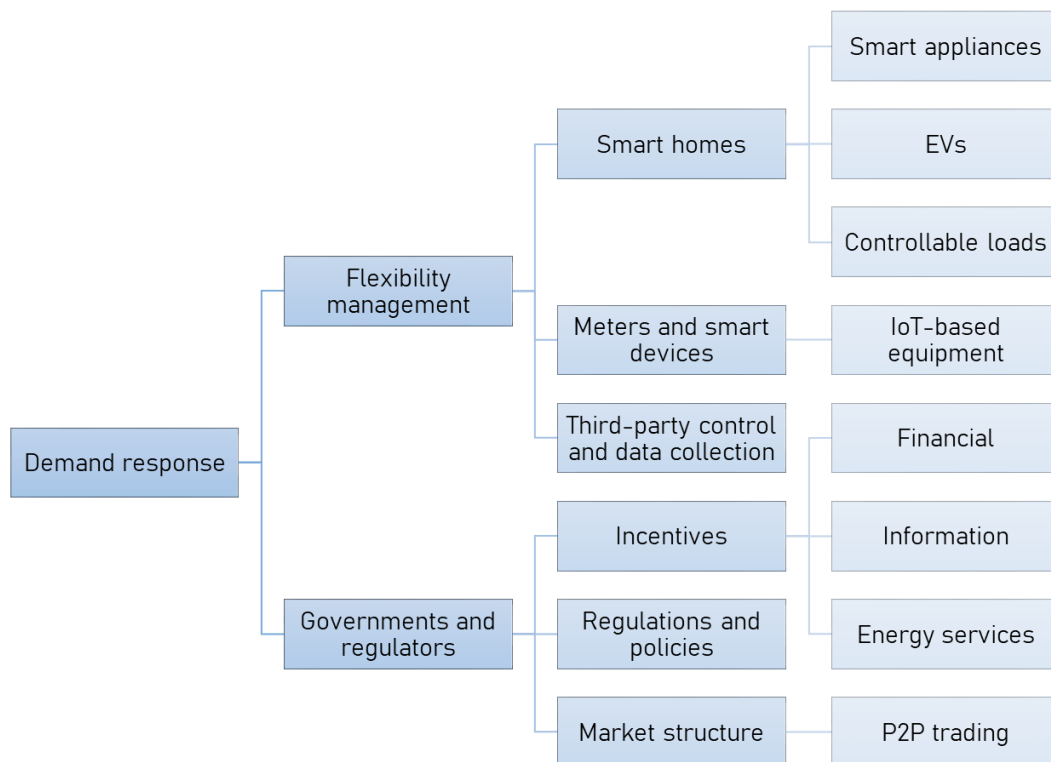


Figure 1. Demand response implementation.

### **2.1.1 Flexibility management**

The balancing of the power grid is currently achieved by adjusting production to match consumption. Increasing renewable energy sources such as solar and wind are difficult to forecast accurately and cannot be controlled in the same way as fossil-fuel power plants. This means that the flexibility needs to come from the storage-solutions and demand side-solutions. According to Immonen et al, (2019) the one way to conduct this flexibility management are batteries, but with current technologies this solution is not feasible cost-wise and batteries waste more natural resources in comparison to managing the demand-side using existing flexibility resources. Therefore, it is important to exploit all existing flexibility resources from demand side such as electric heaters, HVAC (Heating, Ventilation and Air Conditioning system), water boilers, and different smart appliances. Immonen et al (2019) have presented that consumers could provide their home devices and energy storage directly as flexibility potential for being active participant in the energy market. This is resulting in the need for real-time mechanisms for flexibility management and new service providers that take care of functionality between households and the market. For example, aggregators, virtual power plant operators, and technical service providers have the potential to play an important role in future energy markets (Immonen, Kiljander, & Aro, 2019). Also, the International Energy Agency has stated that great promise for enabling demand-side flexibility are new business models such as aggregation, virtual power plants (VPPs) and other distributed energy resources.

One enticing way of implementing the demand response is the utilization of the batteries of the increasingly popular electric vehicles (EV). The batteries of the cars can be charged when the prices of the electricity are low, and the batteries can be discharged back to the network when prices surge. Simulations show that under suitable conditions this kind of system may provide basically free electricity for the operation of the EV or even generate considerable profit from the selling of the electricity even when considering the investment on the required equipment and wear on the batteries. (Li, Chowdhury, Bhavsar, & He, 2014)

### 2.1.2 Smart homes

In order to properly implement the demand response management (DRM) we first need to have controllable devices at the residential buildings, and the buildings need to be connected to the external world (Lai, Zhou, Hu, Zhou, & Zhong, 2015). Residential buildings have been slowly filling with various smart and connected gadgets and appliances since the first futuristic American concept homes of the 30s (Darby, 2018). This trend has been picking up speed in the last decades due to technological advancements (Darby, 2018) and a recent study released by the electronics manufacturer Xiaomi (Wakefield Research, 2021) showed that more than half of the surveyed US customers had purchased at least one smart device during the COVID-19 pandemic.

In addition to making the life of the residents easier and more comfortable, these so-called smart homes (SH) may also have the potential participant in the operation of the electrical grid more than ever. Smart homes may generate power and offer the ability to externally adjust the level of power consumed by the building. (Darby, 2018) Smart homes, with their various connected devices and continuous internet connections provide an ideal bridge between the electrical network and demand response implementation, enabling the smart homes to function as part of the smart grid (Lai et al. 2015). To further increase the deployment of smart homes, Lai et al. (2015) also advocate for a large-scale deployment of the fiber power cable to the home (FPCTTH) which combines residential power delivery cabling to the fiber optic cabling used for example for internet and TV.

Several sources can be found in the literature regarding the simulation of various demand response systems in smart homes. For example, Gudi, Wang, Devabhaktuni, & Depuru (2010) have used Java language to develop a simulator which a particle swarm optimization (PSO) in order to create a schedule for various home appliances so that the simultaneous power consumption and the price of the electricity would be as small as possible. Further expansion to this work was provided by using Matlab from Tsui & Chan (2012) who utilized convex programming (CP) while also integrating parameters regarding how the users accept the various appliances being off, i.e. for example the resulting increase in the temperature while the air conditioning is not operating. N, V, & Radhika

(2015) presented an idea of a centralized controller which utilized Matlab programming and game theory's algorithms for scheduling loads of various appliances at home.

Hoosain & Paul (2017) implemented a prototype of a tier-based smart plug system, in which the users can connect different types of appliances to the grid based on their importance and then the utilities can remotely shut down various devices based on the criticality of the power shortages. The system also included an option for the users to definable timetables for indicating the times at which they wanted certain appliances to be excluded from the demand response system.

Fernandes, Morais, Valea, & Ramos (2014) described a system called Supervisor Control and Data Acquisition House Intelligent Management (SHIM), developed at the Institute of Engineering — Polytechnic of Porto (ISEP/IPP). This system is able to simulate various functionalities of a smart home, connect to the real world, and control actual hardware. The authors implemented a demand response functionality to the simulator and introduced the concept of a dynamic load priority (DLP). In DLP, the priority of the various loads in the system can change during a DR event instead of remaining fixed. For example, a refrigerator which has just executed its cycle gets a low priority and the priority keeps increasing when the temperature inside the refrigerator increases closed to a critical limit.

Wang et al. (2013) presented an interesting idea for taking advantage of the thermal inertia of a smart home for shifting the scheduling of an air conditioner. In this work, thermal energy inside a house is considered a type of virtual energy storage system. They used a mixed-integer programming language (MILP) for optimizing the schedule. The same methodology could likely be also used for heating.

### **2.1.3 Meters and smart devices**

A smart metering system is an electronic system which is capable of measure electricity feed into the grid and consumed electricity from the grid. The system is able to transmit and receive information, monitor and control. The system brings benefits for the energy system and the users for example with smart meters, consumers are able to get regular

measurements of their energy usage. Smart meters can also provide almost real-time feedback on energy consumption and enable consumers better manage their energy usage, saving energy and lower the electricity bill. For those consumers that are interested to be actively involved in the electricity market, smart meters can offer even more for example allow to adapt the energy usage to different energy prices during a day and enable to consume when the prices are at lowest. Smart meters are also relevant to those consumers who generate electricity for example by solar panels. A smart meter can measure the electricity that household supplies to the grid and inform the grid manager. For network operators one benefit is that operators receive more precise information about activities in different parts of the network. Thus, operators can better allocate the investments and manage their infrastructure to fulfill the requirements of the customers. (European Commission, 2020)

According to Immonen et al, (2020) consumers incentives to invest in meters and smart devices that allow the third party to control their devices are financial savings; saving energy; environmental benefits and ecology; residential comfort and conditions; smart home, making everyday life easier; monitoring and reporting electricity consumption.

Immonen et al, (2019) have identified different obstacles to invest meters and smart devices. Financial obstacles are high investment costs, too small incentives, too long pay-back time and contract issues. Other obstacles are identified as safety and reliability of devices, security issues, difficulties in installing devices, compatibility issues and lack of experience. (Immonen, Kiljander, & Aro, 2019). Touquet & Alaton, (2020) have also stated in their report for the European Commission that data privacy is a considerable concern among consumers. They have also indicated that consumers are concerned about electromagnetic radiation and the broader impact of smart meters on health. (Touquet & Alaton, 2020)

#### **2.1.4 Third-party control and data collection**

According to Immonen et al, (2019) consumers would allow third party controlling their home devices if it occurred without disruption and if it is beneficial to the consumer and the most preferred is a discount in electricity bill or some other financial compensation.

In addition, concerns about the environment and the reduction of emissions are increasingly motivating consumers. Also, some services such as automatic heat control and network reliability are interested consumers. In the research are also identified concerns about third party controlling and these are: desire to maintain control; insecurity of the Internet; lack of experience/knowledge; costs vs. benefits; problems and uncertainty; data collection and utilization; objectives and motives; concern about the property; contracts; stuck with the same provider. (Immonen, Kiljander, & Aro, 2019)

Immonen et al, (2019) are identified issues that should be taken into account in data collection: security, data privacy and data protection regulation (GDPR); trustworthiness of the data collector; disclosure of information forbidden without the consent of consumer; consumers' access to their own data; consumers' want to decide what data is collected about them and what purposes it can be used and only collecting relevant data.

## **2.2 The role of operators, governments and regulators**

To help consumers respond to price signals or signals from system operators, governments and regulators should study the feasibility of using ICT platforms and smart contracts. Governments and regulators should also develop flexibility offerings and implementing time-based rate programs as well as regulatory structures that monetize flexibility at the point of use. Governments should also promote consumer and third-party access to smart-metering data and dynamic pricing and other signals. (International Energy Agency, 2020)

According to the Council of European Energy Regulators, (2020) the key principle in tariff design is cost reflectivity that leads to economic efficiency. Other principles are non-distortion, cost recovery, non-discrimination, transparency, predictability and simplicity, and regulators need to find a balance between these principles. (Council of European Energy Regulators (CEER), 2020)

Consumers' attitudes towards flexibility management and related services highly rely on incentives and benefits. Financial incentives seem to be the most effective way to change electricity consumers' behavior but also awareness about energy markets, environmental issues and energy consumption are increasingly interesting to people. New business models are required to enable the consumers to become an independent actor in the new energy markets. (Immonen, Kiljander, & Aro, 2019)

### **2.2.1 Incentives**

#### Financial

Many research have indicated that financial incentives seems to be the most effective way to change electricity consumers' behavior and to engage them to participate in demand flexibility. (Verbong, Beemsterboer, & Sengers, 2012)

Immonen et al, (2019) presented in their research that the electricity consumers rationalized their refusal on the basis the costs caused by the device and system investments should be paid by the party that gains the most benefit for the example electricity company, the DSO, the controlling party or the service provider. They think that consumer should somehow receive their share of the forthcoming benefits and that government support was also required for example tax reliefs.

#### Information

Kendel, Lazaric, & Maréchal (2017) study showed that detailed feedback on the energy consumption helped the electricity consumers to understand their behavior and the structure of their consumption and helped them identify the inefficiencies in their consumption. The results of their research show that all participants reduced their electricity consumption and the main reasons for that seemed to be direct learning from feedback about the consumption and/or indirect learning through self-monitoring. Although, the learning can occur also by intrinsic motivation without any external feedback. In the study was highlighted that the fully engagement of participants was an important aspect

to reductions in electricity consumption. The experiment revealed some sources of over-consumption and participants become more aware of their potential wasting of energy (Kendel, Lazaric, & Maréchal, 2017). Verbong, Beemsterboer & Sengers, 2012 have also noticed that providing consumers detailed feedback on their electricity consumption will lead to a reduction in energy use.

Immonen, et al, (2019) have identified in their research how the electricity consumers follow price developments and events in the electricity market. According to research the most used data source are newsletters of electricity company. Other well-used information sources according to the research are the Internet and other general media. Furthermore, information is obtained by using the application of TSO of hourly prices, inspecting the electricity bills and information that comes from offer requests from electricity companies. Electricity consumers need also information about demand flexibility and encouragement to become active participants in the energy market. (Immonen, Kiljander, & Aro, 2019)

Gangale et al, (2013) have studied consumer engagement in smart grid projects in Europe. The aim of the research was to collect information about key aspects of customer engagement. According to their research to engage customers need to raise awareness and provide information about new technologies. In order to change consumer behavior, consumers need to be aware of their energy consumption and how it affects the environment, energy security and potential money savings. Although, information and feedback are not necessarily enough to change consumer behavior. Energy providers need to build trust and put consumer motivations in center when making decisions. (Gangale, Mengolini, & Onyeji, 2013)

### Energy services

Different energy services can be considered as incentives and according to Immonen et al, (2019) the most interesting energy services among electricity consumers are monitoring electricity prices and optimizing own consumption; automatic advance detection

of electrical equipment malfunction; automatic heat adjustment; guidance services and electric car charging services. (Immonen, Kiljander, & Aro, 2019)

### **2.2.2 Regulations and policies**

The use of digital technologies in the energy sector causes new risks that need to be addressed through safety, security and liability policies. It requires collaboration from regulators to address the new complexities that are caused by flexible electricity services. (The European Consumer Organisation, 2018)

Electricity consumers would be interested to sell their surplus electricity to their neighbors and self-producing communities but when Immonen et al, (2019) wrote the article it was not possible (at least in Finland) due to legal constraints. In addition, moving the time of consumption is not profitable with current taxes and transmission costs because these costs stay at the same level, only the energy itself may be cheaper. (Immonen, Kiljander, & Aro, 2019)

According to Zepter et al, (2019) European Commission aims to actively reduce the regulatory barriers to promoting consumers to participate in the electricity markets. (Zepter;Lüth;Crespo del Granado;& Egging, 2019)

### **2.3 Peer-to-peer (P2P) trading**

Prosumers can actively participate in the energy market by a new energy management technique for smart grid called peer-to-peer (P2P) trading. Prosumers can gain benefits by selling their excess energy to other consumers or by reducing the demand for energy. P2P trading can be also beneficial to generators, retailers, and distribution network system providers because of decreasing peak demand, lower investment and operational costs, reducing reserve requirements, and improving power system reliability. However, P2P platform is an untrustworthy system because it is expected that prosumers will trade their surplus energy with one another with a very low influence from a central controller.

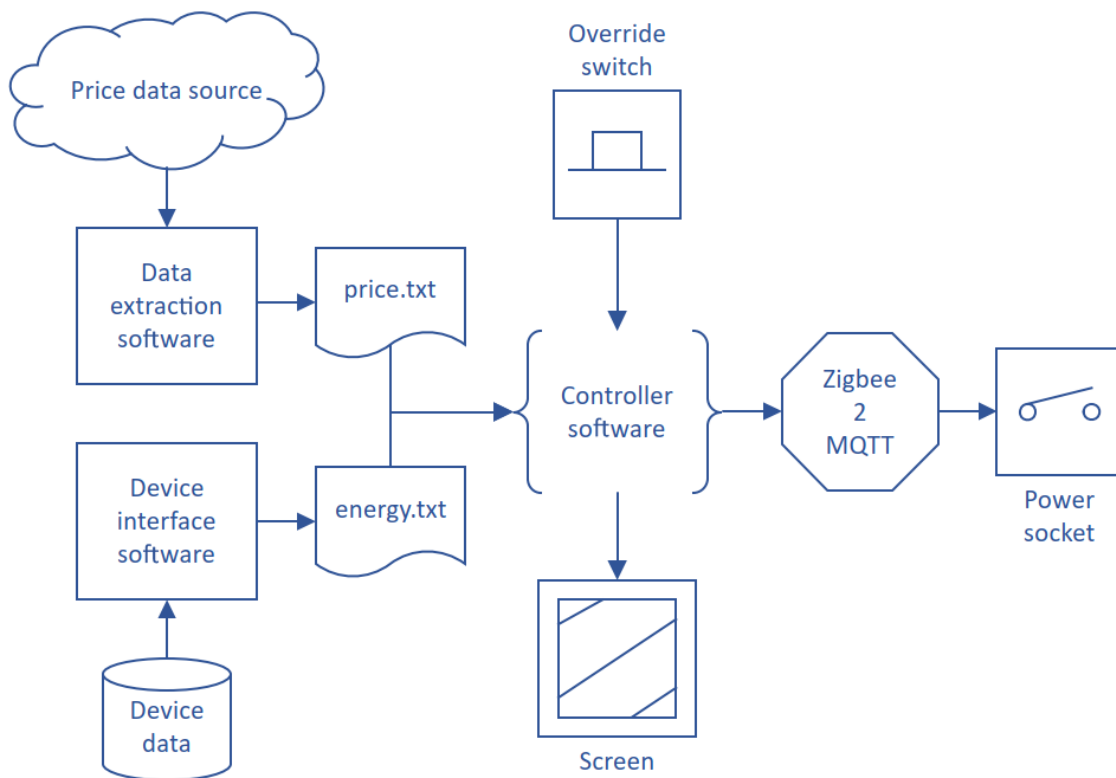
Also, the large number of users cause challenges to model the decision-making process parameters that are affected by rational choices of prosumers that might conflict with the interest of other prosumers in the network. (Tushar, Saha, Yuen, Smith, & Poor, 2020)

Zepter et al, (2019) have modeled a market design that allows the participation of community of prosumers in the day-ahead and intraday markets. In the model, prosumers use P2P trading and battery storage to balance generation and load within the community and to maximize the use of wind and solar power generation. Their model aims to minimize expected costs for electricity consumption within the community. The model takes into consideration supply-demand balancing decisions, trade restrictions and rules on local P2P trading and restrictions for the physical boundaries of storage systems. The electricity supply in this case coming from four possible sources: direct wind/PV consumption, electricity grid consumption, storage discharge and P2P purchases. According to the simulation, when combining P2P trading and storage solutions, most of the demand can be met within the community and grid consumption seems to be necessary only during evening peak hours. (Zepter; Lüth; Crespo del Granado; & Egging, 2019)

### **3 Smart home demand response simulation**

The works in the reviewed smart home demand response related literature seem to assume that the price of the electricity is either known beforehand or that the cycling of the power of the devices at the residential location is directly controlled as an ancillary service by an external party. It is true that in practice the prices might be known in advance within some timeframe, for example in the case of the Nord Pool's day-ahead prices or other similar systems, but this might not be the case everywhere. We wanted to consider the case where either the price is not known in advance or the information is not available for some reason, for example due to being in a remote location without an internet connection. What can the end-user do in this case if they want to optimize their power consumption? Forecasting the price of electricity has certainly been researched a lot and complex algorithms likely exist, but is it possible to develop some naïve and computationally light approach which would yield adequate results?

We wanted to consider the case of charging an EV at home and optimizing the schedule in order to save on the cost of the electricity. We chose this firstly because the authors of this work are using a 2015 Nissan Leaf EV for their daily driving and thus this subject is interesting on a personal level. We also chose this as being fairly complex case, if the developed system is able to optimize the electricity cost for the EV, the same system should be fairly easily applicable for other more simplistic devices such as laundry machine or water heater. The core components of the proposed intelligent charging controller are shown in Figure 2.



**Figure 2. Core components of the proposed intelligent EV charging.**

In order for the intelligent charging system to be useful and convenient to the users, the system probably should have some indication as to its current status and the timing of the charging. The user interface would be naturally implemented through to an existing smart home system in case the intelligent charging controller is integrated into such a system. The output of the controller software is a control signal, which is used to enable and disable the charger. In case this system is integrated directly into a charging unit, this could likely directly control an output relay of the charger. However, in order to remain as generic as possible, the output from the software could also be used to control a remote power socket.

The controller software itself resides at the heart of the implementation. This software needs to be able to read the input files, produce graphics to the screen, send control signals as outputs. One integral part of the software is the maintaining of the price information. A similar structure based on the spot prices was used as in the previously described sections and the day-ahead spot-price information needs to be loaded from a file provided daily to the software, but in addition to the day-ahead prices the software also needs to be able to maintain the price information for the ongoing day. The software

needs to detect when new data is available in the input file, it needs to take into account the changing of the day, and it's very useful if the software is able to maintain its state over host system restarts.

In a stand-alone solution (in case the intelligent charging controller is not integrated into some third-party home automation system), the controller software can be implemented to for example some embedded platform.

The simulations in the literature aim to be (or at least they should be) generic and provide universally applicable results. We wanted to focus specifically on the electricity contracts locally available residential customers. Thus, we included in our simulator the pricing schemes from the local supplier (Vaasan Sähkö Oy) and the day ahead Nord Pool spot pricing for the region of Finland. The results of this work might be also more broadly applicable, but the specifics of this work were selected purely for personal reasons.

Li et. al. (2015) argue that most of the vehicles are parked and available for plug-in for most of the day. However, we would highly question this statement; even though vehicles are in general not in use for most of the time, they are not necessarily available for plug-in other than when specifically parked at a charging station or at home where the charger is available. Charging stations at workplaces or public locations are not very common yet and for example the sockets present in the parking spaces in Finland are only intended to be used with motor heaters, thus usually not either capable or allowed to be used for charging BEVs. This is something we wanted to take into account in our simulations

### **3.1 Nord Pool spot prices**

For the purposes of implementing the simulator, the Nord Pool spot prices for Finland were extracted and analyzed. The following section describes this process in more detail.

Nord Pool is the power exchange for Nordic and Baltic countries. At the time of writing this, the Nord Pool website offers a public record of the day-ahead prices spanning back to the beginning of 2019. The prices for the following day are typically published at 12:42

CET. The available data can be manually viewed and downloaded one week at a time from the Nord Pool website. Automatic extraction of the data (and/or use for commercial purposes) is prohibited under Nord Pool. The site claims that the data is available in Excel format, but closer inspection of the downloaded files shows that the content is actually in HTML format.

The data available on the Nord Pool website contains the following for each day; 24 hourly spot prices, minimum price, maximum price, average price, peak, off-peak 1 and off-peak 2. An object structure was created reflecting this data. The class definition in C# is shown in Figure .

```
public class DayAhead : IComparable
{
    public DateTime Date = DateTime.MinValue;

    public float[] Prices = { float.NaN, float.NaN, float.NaN, ...

    public float Min = float.NaN;
    public float Max = float.NaN;
    public float Average = float.NaN;
    public float Peak = float.NaN;
    public float OffPeak1 = float.NaN;
    public float OffPeak2 = float.NaN;

    public DayAhead() {}

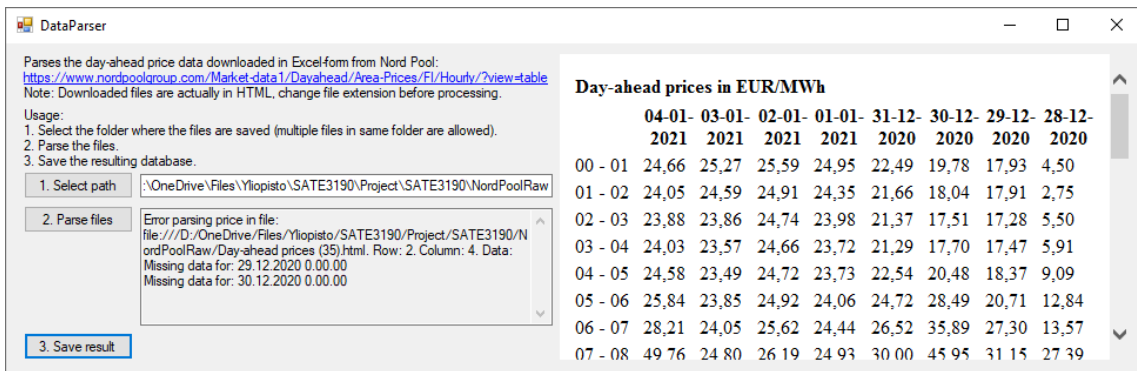
    public int CompareTo(object obj)
    {
        if (obj == null || !(obj is DayAhead))
            return 1;

        return DateTime.Compare(Date, (obj as DayAhead).Date);
    }
}
```

**Figure 3. Object model representing the Nord Pool day-ahead price data.**

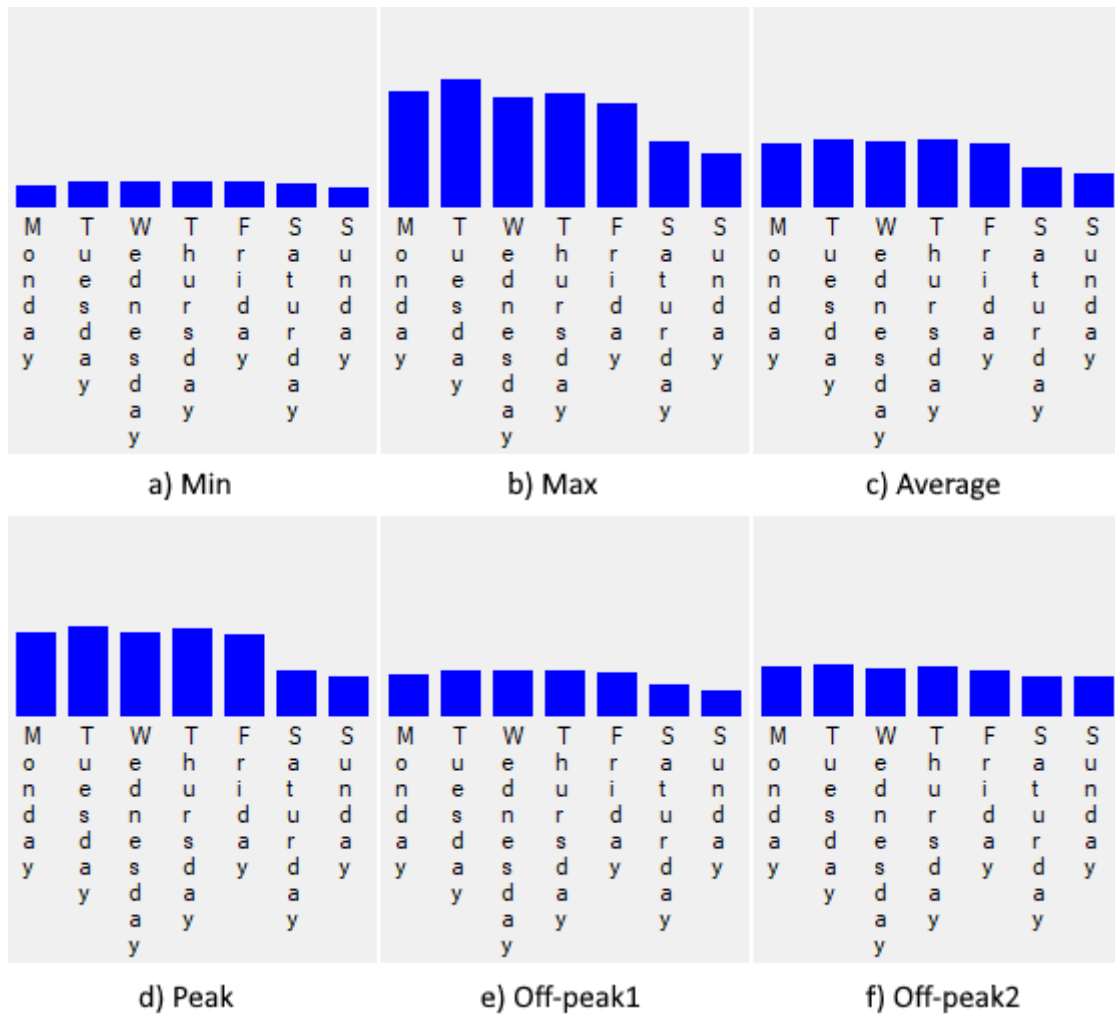
The day-ahead price history for Finland was manually downloaded from the Nord Pool between the duration of 18.11.2019-4.1.2021. The authors of this work wanted to include at least one full calendar year worth of data for the purposes of this project. Further analysis of a larger dataset might yield more accurate results or additional insights regarding the data, but these were deemed to be outside the scope of this work.

A tool was then developed for extracting the data from the raw Nord Pool files into the object structures mentioned previously. The tool assumes that the files are either directly downloaded from the Nord Pool (HTML content with .xls file extension in which case it tries to rename the files to .html) or that they have already been renamed to .html. The tool then proceeds to read all the values from the provided files and constructs an object database based on the found data. After data extraction, the tool performs a simple error correction for missing data and sorts the objects based on the date in descending order. Finally, the database can be saved in an XML format. The data parser tool is shown in Figure .



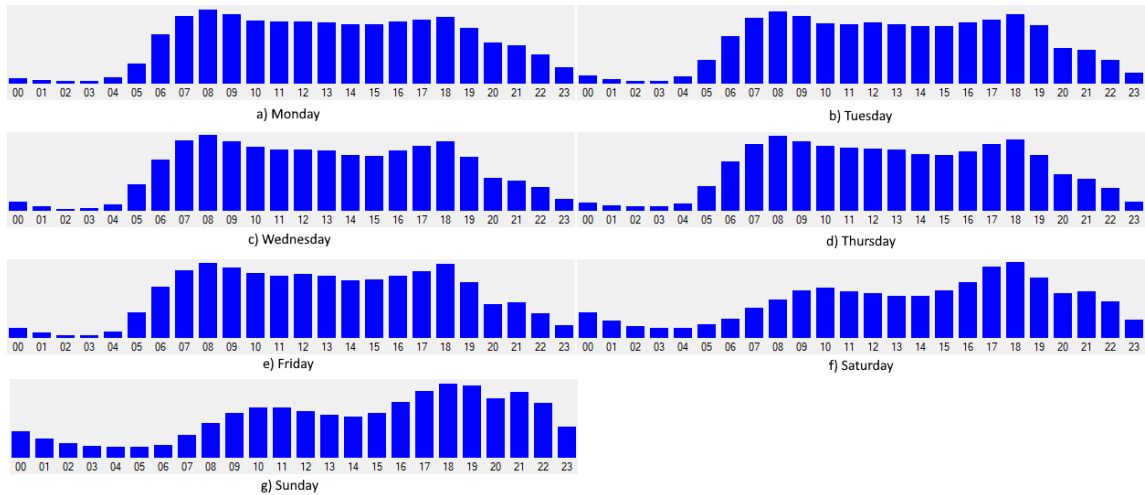
**Figure 4. Program developed for parsing the spot price data downloaded from Nord Pool.**

After extracting the data, another tool was developed for analyzing the gathered data. This tool starts by taking as an input the database created by the previously mentioned tool and then goes through all the available data. The analyzer tool calculates averages of the minimum, maximum, peak, etc. prices for each day of the week. The tool also calculates hourly weighted averages for each day. The daily averages of the different values are shown in Figure .



**Figure 5. Averaged daily electricity price data from Nord Pool for the Finnish region. a) Minimum price, b) Maximum price, c) Average price, d) Peak price, e) Off-peak1 price, and f) Off-peak2 price.**

From these we can determine, that on average, the electricity seems to be cheapest on Saturdays and Sundays as the maximum, average, and peak values are highest between Monday and Friday. However, based on the minimum and off-peak values, cheap electricity might be available during any day of the week.



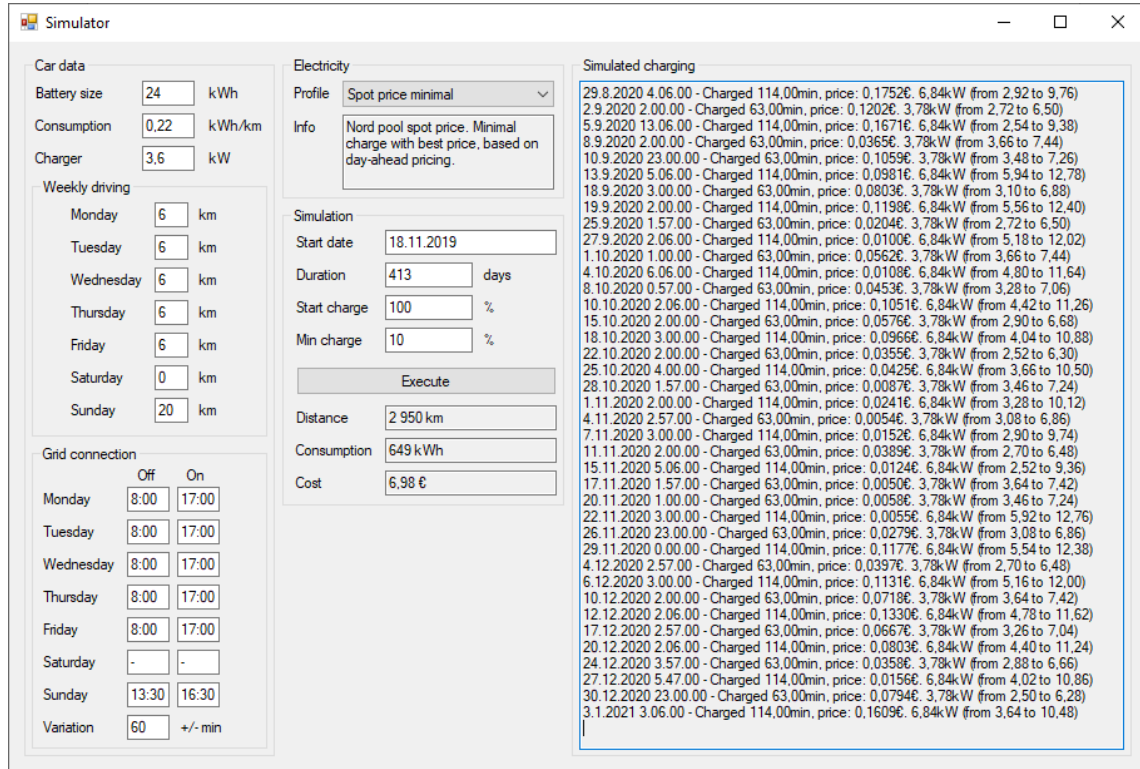
**Figure 6. Normalized average hourly electricity prices from Nord Pool for the Finnish region. a) Monday, b) Tuesday, c) Wednesday, d) Thursday, e) Friday, f) Saturday, and g) Sunday.**

The weighted averages of the hourly prices for each day of the week are shown in Figure . The diagram for Monday-Friday look all fairly similar with only minor variations. Diagrams for Saturday and Sunday however seem quite different from the rest. From these diagrams we can determine, that on average, the cheapest electricity is available on weekdays approximately six hours between 23:00-04:59. During Saturdays this window is slightly sifted to approximately between 01:00-05:59 and one hour even later during Sundays. Figure shows a strange jump in the price between 23:00 hours on Friday and 00:00 hours on Saturday, this is however just due to the fact that daily weighted averages were used for the calculation and the prices on Saturdays are in general lower than the prices on Fridays. If weekly weighted averages were used instead, this jump would not be present in the diagram.

### 3.2 EV charging simulator

An EV charging simulator program was developed for the economics of charging an electric car under different conditions. The program can be used to simulate the depleting and charging of an electric car based on the habits of its user. The program contains several different profiles related to power economics, and the implications of these can

be evaluated under the specified conditions. An image of the simulator is shown in Figure 7.



**Figure 7. EV charging simulator, default settings and output after running the simulation.**

The program tries to automatically load the Nord Pool spot price database mentioned in the previous chapter and it takes as inputs several parameters regarding the car and its usage. The battery size and charger capacity are taken from a standard 2015 Nissan Leaf equipped with the basic onboard AC charger (no quick charge or DC charging) intended for home use from a normal 16A wall outlet.

The simulation software also takes as inputs the energy consumption (kWh per km), the average driving distance for each day of the week, and the times at which the car may be disconnected/plugged into the grid (**Grid connection Off** specifies the time at which the car is disconnected from the charger, while the **Grid connection On** specifies the time at which the car may be connected back to the charger, **dash or other non-time**

**value** can be used to indicate that the car remains plugged for the entire day). The latter two of these depend purely on the driving habits of each individual user and the consumption varies heavily depending on various factors such as the climate in which the car is being used/stored, amount of the cabin heating/cooling, and the type of driving (heavy/light on the gas/breaks, city/highway, etc.). The default values of the simulator are based on the actual usage of the author of this work.

The user of the simulator can also specify the starting date of the simulator, duration of the simulation in days, the starting charge of the battery when beginning the simulation, and the minimum charge under which the simulator tries to maintain the level of the battery considering the daily driving figures. The start date and duration are automatically taken from the automatically loaded Nord Pool spot price database. Some simulations can be run outside this range, but some require that the specified dates can be found from the price database.

The simulator functions by taking the start date with the provided starting battery charge. The simulator then steps through each day within the selected timeframe, decrementing the battery charge level based on the daily driving habits described by the user. At the end of each simulated day, the simulator checks whether the following days driving will drain the battery under the specified minimum charge. In case this condition is detected, the program tries to simulate battery charging within the grid connection times provided by the user. By this behavior, the program does not assume that the car would be plugged into the grid and charged fully every day (as this probably is not how EV users generally behave), but instead the program attempts to simulate the fact that the user likely knows how much they are going to use the car in the near future and when the battery should be charged in relation to that.

The most interesting configurable simulation parameter is the electricity profile, which affects the cost of charging and the more precise time window within which the actual simulated charging takes place. This is further explained in the following chapter.

The program produces as an output the distance of the simulated driving, consumed electricity, and electricity cost under the selected profile. The program also outputs the time, price, and amount of power for each simulated charging event.

### **3.2.1 Electricity profiles**

The simulator contains a total of seven individual electricity economical profiles used for charging the EV. The first of these is the fixed price single tariff profile from the local electricity reseller; 5,19 c/kWh “Yleissähkö – Perussähkö” from Vaasan Sähkö Oy. This is the most simplistic profile and under this the charging is simulated always starting from the moment of the EV being plugged into the grid.

The following two profiles are slightly more complicated; they simulate the double tariff electricity from the local reseller; “Yösähkö – Perussähkö” from Vaasan Sähkö Oy, 5,53 c/kWh between 7-22 and 4,67 c/kWh between 22-7. The first of these two profiles simulate the charging starting always at the grid connection, but the latter delays the charging to start at 22:00 hours with the cheaper nighttime tariff.

The fourth available electricity profile assumes that the user is able to buy electricity-based directly on the Nord Pool spot prices. Electricity supply contracts as these are available in Finland, such as the “Aktiivi” from Oomi Oy. In this profile the simulated charging happens immediately after grid connection with the spot price of the hour, and the price changes at every hour when the charging proceeds.

The last three profiles leverage also the Nord Pool spot prices, but these try to optimize the actual time of charging instead of starting to charge at the time of grid connection. One of these profiles takes a simplistic approach by timing the charging of the EV based on the price trend analysis described in the previous chapter. This is the naïve optimization algorithm mentioned previously. Another profile looks at the minimum amount of charge that needs to be applied to the battery during each charging event in order not

to fall under the specified minimum battery charge, the profile then looks for the window within the grid connection which will yield the cheapest electricity for achieving the calculated charge. The last profile does the same as the previously described, with the exception that it tries to always charge to full instead of just charging the bare minimum.

### 3.2.2 Simulation results

Several different conditions were simulated with the developed tool during its development. The most interesting of these are listed in Table 1. The columns indicate the selected power profile in a shortened form. These stand for Local **single** tariff, Local **dual** tariff, Local **dual** tariff **optimized**, **Spot** price, **Spot** price **trend**, **Spot** price **minimal**, **Spot** price optimal **full**. The rows correspond with different amounts of driving. The **low driving** amount represents driving profile as shown in Figure 7 (6km on Monday-Friday, 0km on Saturday, 20km on Sunday), total 2 950 km and 649 kWh. The **medium driving** amount is quadrupled the low drive (24km on Monday-Friday, 0km on Saturday, 80km on Sunday), total 11 800 km and 2 596 kWh for the simulated timeframe. Corresponding with roughly 11 800 km yearly driving. The **high driving** amount is probably pushing what is reasonable with the EV in question (45km on Monday-Saturday, 90km on Sunday), total 21 240 km and 4 673 kWh simulated.

**Table 1. Results of the simulations. Electricity cost of different driving amounts simulated with different electricity profiles.**

	<b>Single</b>	<b>Dual</b>	<b>Dual opt</b>	<b>Spot</b>	<b>Spot trend</b>	<b>Spot min</b>	<b>Spot full</b>
<b>Low drive</b>	33,39 €	34,87 €	30,04 €	21,10 €	9,41 €	6,99 €	8,41 €
<b>Med drive</b>	134,73 €	141,94 €	121,23 €	81,86 €	40,33 €	32,89 €	35,70 €
<b>High drive</b>	242,52 €	255,00 €	218,22 €	155,08 €	73,27 €	61,31 €	65,30 €

**Table 2. Relative changes in the cost of electricity from the previously described simulated cases.**

	Single	Dual	Dual opt	Spot	Spot trend	Spot min	Spot full
<b>Low drive</b>	100 %	104 %	90 %	63 %	28 %	21 %	25 %
<b>Med drive</b>	100 %	105 %	90 %	61 %	30 %	24 %	26 %
<b>High drive</b>	100 %	105 %	90 %	64 %	30 %	25 %	27 %

Table 2 lists the values on the previous table in relation to the base price, which is the single tariff electricity from the local reseller. From these we can determine that the dual tariff electricity is a bad idea if one does not also intend to time their EV charging purely to the cheaper night tariff, and even in that case the savings are fairly marginal. Simply by switching to the spot pricing one may save up to 40 % on their electricity, and with slight optimization the total cost can be reduced to  $\frac{1}{3}$  or  $\frac{1}{4}$  of the original. The highest savings can be achieved with the minimal charging scheme, but this will probably also place the most stress on the battery. Spot pricing with a fully optimized charging window is probably the most reasonable, and the naïve trend-based algorithm provides also considerable savings while being easy to implement in the software and not requiring connection to any external system while in operation.

### **3.2.3 Further improvements**

The simulated charger is currently assumed to be 100% efficient, which is not the case in real life. Taking this into account in the simulator would be fairly trivial and thus was left out from this implementation.

Only the price of the electricity itself is considered in the calculation. Various taxes, commissions, monthly fees, and the price of the electric power transmission should also be calculated in order to give the user a better picture of the cost of operating the vehicle. These were also considered to be outside the scope of this exercise.

The simulator also has a parameter for varying the grid connection times. Using this adds randomness to the grid connection times and thus to the resulting total cost under certain electricity profiles. After further consideration it was determined that this parameter is rather useless as is; the varied values should trend towards the fixed (variation set to 0) after an infinite amount of iterations. Instead, the program could attempt to calculate the variation of the resulting total price based on the variations on the grid connection. However, the search space would likely increase exponentially and implementing this in an efficient way is probably quite difficult without employing more sophisticated optimization methods.

The simulator aims to always charge the battery back to the full charge specified by the battery size parameter, but depending on the various input conditions, the simulated battery may also be left in a partially charged state. This does not happen with the default values present in the simulator but may result for example from the case where daily driving consumes the battery more than what can be charged under the specified grid connection times. These conditions were not tested during the development and the simulator will likely start to behave badly if such conditions are being met excessively.

The simulator is not really a “production ready” software. Error cases are not very clearly reported to the user, the software might even crash, and several improvements could be made to the code in order to optimize the execution times. However, it was not the goal here to develop a commercial grade software, but instead more a proof-of-concept type testing tool.

## 4 Conclusions

The consumer role in the future energy market will increase but energy market actors need to decide how to encourage and motivate consumers to become active players in the market. Consumers need guiding and supporting as being an active member of the energy market.

Consumers' attitudes towards flexibility management and related services highly rely on incentives and benefits. Financial incentives seem to be the most effective way to change electricity consumers' behavior but also awareness about energy markets, environmental issues and energy consumption is increasingly interesting to people. New business models are required to enable the consumers to become an independent actor in the new energy markets. For example, aggregators, virtual power plant operators, and technical service providers have the potential to play an important role in future energy markets.

There are still multiple challenges that need to be addressed before consumers can actively participate in energy markets. For example, although both the smart grids and homes have already been a hot research topic for a while and are also becoming more and more common in practice, there seems to be a total lack of standardization regarding the communication protocols and interfaces which would be required in order to connect the two of these for enabling the implementation of demand response. Several technologies and implementations have been proposed for solving this, but there does not seem to be one preferred over the others.

An EV charging simulator program was developed for evaluating the economics of charging an electric car under various conditions. One of the goals of this work was to explore and evaluate whether a naïve scheduling algorithm could be developed in such a way that savings in the electricity cost could be achieved even without having the utilities directly controlling the scheduling. In the simulated cases we observed considerable savings even in the case when where foresight regarding the development of the electricity

price was lacking. The methodology could likely quite easily be applied to any schedulable electricity needs, in addition to just the EV charging.

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