Stochastic Load Modeling of High-Power Electric Vehicle Charging - A Norwegian Case Study

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***Abstract*—In recent years, the number of electric vehicles (EVs) has increased rapidly. Due to technological advancement, government policies and the focus on reducing greenhouse gas emission, the growth can be expected to continue. Home charging of EVs will often be sufficient for short-distance travel and daily routines. However, EVs still have a limited range. Thus, for long-distance travel, a network of fast charging stations (FCS) is needed. The stochastic nature, high power demand and short duration of EV fast charging, make it in many cases a grid capacity issue rather than an energy issue. Therefore, knowledge about the load profile of FCSs is important. In this paper, a model is developed for the simulation of the aggregated load profile of an FCS. The FCS load model includes a mobility model based on actual traffic flow, EV charging curves and temperature-dependent EV efficiency. Simulations are performed using the Monte Carlo simulation technique, to get a daily load profile for the FCS. Real-world data for the studied FCS in Norway is compared with the results from the simulation to analyze the performance of the FCS load model. The developed load profile for the FCS has a high peak-to-average power ratio, which indicates that the socioeconomic profitability of fast charging stations still is low.**

***Index Terms*—Electric vehicle (EV), Fast charging station, Load modeling, Monte Carlo simulation, Traffic flow, Case study**

I. Introduction

A. Motivation and Background

Globally, the transport sector accounts for 25 % of the world's CO2 emissions [1]. Road vehicles are responsible for the majority of these. They are also accountable for 80 % of the rise in greenhouse gas (GHG) emission from the transport sector from 1970-2020 [2]. Electrification of the transport sector will play an important role to reduce the GHG emissions from the sector, and combat climate change. However, there are some barriers to overcome. Electric vehicles (EVs), here defined as electric cars, have limited range, long charging time, and they are expensive. However, with the introduction of fast charging stations (FCS), the charging time will be heavily reduced. In addition, with the advancements in battery technology, the range is increasing. Nevertheless, an FCS network is necessary to allow for long-distance travel [3].

FCSs present a new type of electric load for the distribution grid. Therefore, accurate models for the load of the FCS are necessary to study its impact on the distribution grid, as well as to determine the optimal placing and sizing of new FCSs.

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B. Relevant literature

The arrival of the EVs to the FCS is one of the key factors in modeling the load of the FCS. The state-of-the-art literature uses different approaches to model the arrival rate at the FCS. Predefined arrival rates are used in [4]–[6]. Both [4] and [5] use a predefined arrival rate based on arrival time distribution of internal combustion engine (ICE) vehicles at gas stations. The daily expected number of EVs visiting the FCS is then used with the hourly arrival rate, to determine the hourly expected number of EVs. The expected number of EVs is then used as an input in a Poisson algorithm, to get the actual number of visiting EVs and the time of their arrival. A simpler approach is used in [7], where the number of visiting EVs each hour is predefined.

In [8]–[15], a mobility model of the EVs is built based on statistical data or local traffic flow. Data from the National Highway Transport Survey (NHTS) is used to build a mobility model in [8]–[12]. This is a US-wide survey, recording information about the number of trips each day, departure and arrival time of each trip and the length of each trip. Based on the statistical data, a mobility model is built. The EVs are initialized with a state of charge (SOC) and battery capacity, and the driving data (number of trips, distance of each trip and speed) is generated. Two approaches are used for building the mobility model, either directly sampling from the recorded data [8]–[12] or building a statistical distribution based on the recorded data [8]. The EV will charge at the FCS if the SOC goes below a certain limit before a trip is completed. A drawback of using the NHTS data is that it is based on driving data for the whole US, which does not necessarily reflect local mobility patterns in the area where the FCS is located.

Local mobility patterns were included in [9], where the distribution of vehicles on the road was used to determine the load profile of the FCS. The percentage of vehicles on the road was divided into intervals, and each interval corresponded to an arrival rate of EVs at the FCS. In [13], the traffic flow from the highway where the FCSs were placed was used to determine the arrival of the EVs. SOC, driving efficiency and battery size were varied. Monte Carlo simulation (MCS) was then used to obtain aggregated and individual load profiles for the FCSs.

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C. Contributions and Organization

From the literature review, only [13] use local traffic flow to create a mobility model. However, the study lacks data from actual EVs, and therefore has employed MCS to model the different parameters of EVs. This is a recurring problem in the literature due to the low adaptation of EVs in many countries.

In this paper, on the other hand, traffic flow data from a real road system and local EV penetration form the basis for the development of the mobility model. Due to the wide-spread integration of EVs in Norway, a realistic representation of the actual EV fleet can be implemented. The main contributions of the work presented in this paper are as follows:

- The mobility model developed in this paper is based on the actual traffic flow of the highways in the system. Together with the local EV penetration, an accurate flow of EVs in the system is developed.
- A realistic representation of the EVs on the road, which captures the different battery size, driving efficiency and charging curve of the EVs, is used. SOC dependent charging curves for each individual EV are implemented in the charging model.
- A temperature-dependent driving efficiency, to account for changes in EV driving range due to the outside temperature, is implemented.
- The study includes a comparison between charging data from an actual FCS in Norway and simulated data.

This paper is organized into five sections. After an introduction in Section I, Section II presents the methodology used to develop the proposed FCS load model. Section III presents the system that is studied. In Section IV, the results from the simulations are compared with the real-world FCS data, and the performance of the FCS load model is discussed. Lastly, Section V concludes the research done in this paper.

II. Load modeling of an FCS

The proposed FCS load model consists of three parts. A mobility model to determine the flow of EVs in the system, a charging model to determine the load demand of the EVs, and a queuing model to account for congestion at the FCS. The different models are combined together in a Monte Carlo simulation.

A. Mobility model

The traffic flow in the model is assumed to be free flow and not congested. Thus, the distance between the cars on the road is uncorrelated. Therefore, the distance and time between cars can be assumed to follow a Poisson distribution [16]. The Poisson process is used to determine the arrival of the EVs to the system. $\lambda(h)$ is the expected number of EVs arriving per minute, for a given hour, h. It is found by equation 1, where $q(t)$ is the actual traffic flow in the system. The waiting time, in minutes, until the next EV enters, is given by equation 2. The variable u is a random variable, uniformly distributed between 0 and 1.

$$\lambda(h) = percentage_{EV} \cdot q(t) \tag{1}$$

$$w = -\frac{1}{\lambda} ln(1-u) \tag{2}$$

Therefore, the first EV for a given hour, h, will arrive at the h hour and w minute. The n^{th} EV will arrive according to equation 3.

$$t_n = t_{n-1} + w \tag{3}$$

The Poisson process for each hour continues until equation 4 is fulfilled. This equation states that EV number $n+1$ arrives in the next hour of the simulation.

$$t_{n+1} >= 60 \tag{4}$$

B. Charging model

1) Generating EVs: The EVs are created randomly based on EV data input. The EV data contains information about a selected number of EV models. This is used to represent the EV fleet. For each EV model in the input data, the battery size, maximum charging power, driving efficiency, charging curve and the probability of selecting each specific EV model are known.

2) Temperature dependency: The outside temperature affect the driving range of the EVs. Nissan [17] and Opel [18] are the only car manufactures, to the best of the authors' knowledge, to have made a range calculator dependent on temperature. Their range calculators are for the models Nissan Leaf and Opel Ampera-e. The relationship between driving efficiency and temperature is nearly identical for both range estimators. Therefore, the Nissan's range calculator is used.

The input to Nissan's range calculator is the number of passengers, average speed and outside temperature. Thus, the range, $D(n_{pas}, v, T)$, can then be calculated dependent on the temperature, where n_{pas} is the number of passengers, v is the speed of the EV and T is the outside temperature. Further, using the size of the Nissan Leaf battery, the temperature-dependent driving efficiency, η_T, can be calculated, as shown in equation 5. Where, E_{bat}, is the battery size of the EV in kWh.

$$\eta_T = \frac{D(n_{pas}, v, T)}{E_{bat}} \tag{5}$$

A scaling factor, β, is calculated for the normal Nissan Leaf driving efficiency, as seen in equation 6. In this equation, η is the driving efficiency published by the manufacturer.

$$\beta = \frac{\eta}{\eta_T} \tag{6}$$

It is assumed that the temperature and range relationship is the same for all the other EVs in the model. Therefore, the β that is calculated for Nissan Leaf can be used to calculate the temperature-dependent efficiency for all EVs, as shown in equation 7.

$$\eta_T = \frac{\eta}{\beta} \tag{7}$$

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3) Charging: An EV has an arrival SOC, SOC_{arr}, when it arrives in the system. The EV will decide to charge at the FCS if the SOC goes below a certain limit, SOC_l, before the EV leaves the system. SOC_l is drawn randomly from a normal distribution with $\mu = 0.30$ and $\sigma = 0.05$ for each EV. Equation 8 shows whether an EV will charge or not.

$$SOC_l > SOC_{arr} - SOC_{loss} \tag{8}$$

SOC_{loss} is the reduction in SOC of the EV when it drives through the system, which is given by equation 9. In this equation, l_{sys} is the length of the system.

$$SOC_{loss} = \frac{l_{sys} \cdot \eta_T}{E_{bat}} \tag{9}$$

If the inequality in equation 8 holds, the EV will decide to charge and the SOC when the EV arrives at the FCS must be calculated. This is calculated with equation 10, where l_{FCS} is the length from the entry point of the EV to the FCS.

$$SOC_{FCS} = \frac{l_{FCS} \cdot \eta_T}{E_{bat}} \tag{10}$$

The amount of energy, E, that the EV needs to charge is given by equation 11. SOC_{upper} is the battery percentage that the EV will charge to, which is assumed to 80 % SOC. This value for the SOC_{upper} is chosen because the charging power that an EV can charge with usually drops after 80 % SOC. Therefore, it becomes less favorable to charge at an FCS. SOC_{FCS} is the SOC of the EV when it arrives at the FCS.

$$E = (SOC_{upper} - SOC_{FCS}) \cdot E_{bat} \tag{11}$$

The charging time of the EVs is determined by equation 12. P_{EV} is the maximal charging power for the given EV. The function α is a representation of the charging curve of the EV. Each EV model will have a unique α, which models the specific charging curve of each EV model. The EVs will not always charge at maximum power. This is controlled by the EVs battery management system and depends on many different factors, such as SOC, outside temperature, the batteries state of health and more. To make it less complex, it's assumed in the charging model that the charging power is only a function of SOC. The data for the charging curves used in this paper is from a Dutch charging network company called Fastned [19]. They have tested different EV models on their FCSs and measured the charging power as a function of SOC. Therefore, α takes the SOC as an input and returns a value between 0 and 1, which determines how much of its maximum charging power capability the EV can charge with.

$$E = \frac{1}{60} \int_0^t P_{EV} \cdot \alpha(SOC) dt \tag{12}$$

Equation 12 has to be solved numerically for the charging time, t_{ch}. By assuming that the EVs charges with constant power for each time increment t, which is 1 minute, both the charging time and demand is calculated. The rated power of the charging point, P_{ch}, can limit the power the EV can charge with. In that case, equation 13 is fulfilled and the EV will charge with the rated power of the charging point.

$$P_{EV} \cdot \alpha(SOC) > P_{ch} \tag{13}$$

It is assumed that charging points have an efficiency, η_{ch}, of 90 %. Therefore, if an EV charges with a charging power of 50 kW, the charging point presents a load of 55.6 kW to the grid.

C. Queuing model

The arrival time of the EV at the FCS is calculated according to equation 14. In this equation, the arrival time to the system, $t_{arr,sys}$, is calculated from equation 3, and $t_{ch,start}$ is the charging start time.

$$t_{arr,FCS} = t_{ch,start} = t_{arr,sys} + \frac{l_{sys}}{v} \tag{14}$$

Then, by using the charging time, t, found by solving equation 12, the departure time, $t_{dep,FCS}$, and charging stop, $t_{ch,stop}$, can be calculated according to equation 15.

$$t_{dep,FCS} = t_{ch,stop} = t_{arr,FCS} + t_{ch} \tag{15}$$

However, if many EVs want to charge at the same time, there will be queues forming, which results in EVs not being able to charge straight away. If there is a waiting time, $wait$, due to queues, the charging start time will be according to equation 16.

$$t_{ch,start} = t_{arr,FCS} + wait \tag{16}$$

The departure time will be according to equation 17.

$$t_{dep,FCS} = t_{ch,stop} = t_{ch,start} + t_{ch} \tag{17}$$

In this queuing model, a variation of the $M_1/M_2/c/k$ model is implemented, where k is a time restriction in the length of the queue, rather than the number of EVs. Full transparency is assumed, meaning that the customers know how long the wait is in the queue for each charging point. The customer will always choose the queue with the shortest waiting time and will leave if the waiting time exceeds k for all the queues. The maximum waiting time in the queue is assumed to be 15 minutes. If an EV arrives and the waiting time is longer than 15 minutes, it will leave the FCS.

D. Monte Carlo simulation

There are several stochastic elements in the modeling of the aggregated load profile of the FCS. Therefore, Monte Carlo simulation is performed in the model, implemented as shown in Fig. 1. Firstly, the deterministic input data to model a representation of the EV fleet is given, i.e. the percentage of cars that are EVs, the number of charging points and their corresponding rated power. Monte Carlo simulation is then performed for a predefined number of iteration. For each iteration, traffic flow and temperature profile for the system

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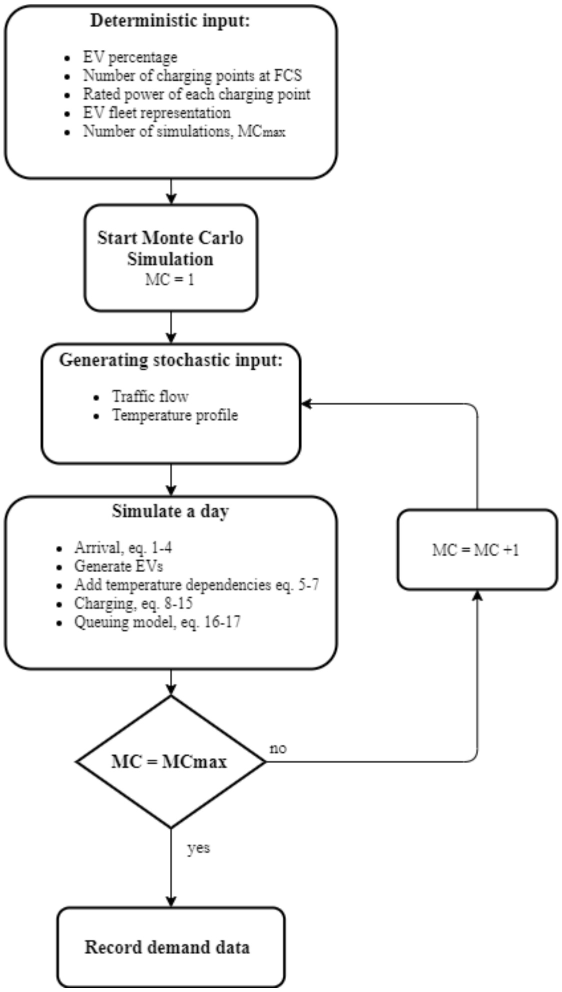

Fig. 1. Flow chart of the proposed method for developing the FCS load model

are drawn randomly from a predefined data set. The load profile for the FCS is then simulated for a day with the use of the equations developed in subsection II-A to II-C. For each iteration, the charging demand for each EV is aggregated to a load profile for the FCS.

III. System description

The system that is studied is the 25 km long highway between Trondheim and Stjørdal in Norway, which is a section of the highway E6. The system is simplified to have only two entry points, one in each end. Therefore, every EV that enters from West leaves in the East, and vice versa. The FCS is placed along the highway, 10 km from the East end and 15 km from the West end. There is already an existing FCS at this location operated by Fortum [20]. The FCS consists of two fast-charging points with a maximum charging power of 50 kW, both supporting the combined charging system (CCS) and CHAdeMO.

1) Traffic flow: The traffic flow is an input parameter and historical traffic flow is used in the mobility model. Traffic data is gathered by The Norwegian Public Roads Administration [21], who has measuring points for traffic flow both at the entry and exit point of the system. The information on when the cars enter the system is used as input to create a mobility model of the EVs in the system. In the mobility model, it is assumed two different traffic flow inputs, one for weekdays and one for weekends. Therefore, for each iteration of the flow chart in Fig. 1, it is a 2/7 chance that the weekend traffic flow will be used and a 5/7 chance for the weekday traffic flow.

The two blue colored lines in Fig. 2 illustrate the weekend traffic flow. The data illustrating the weekend traffic flow is from Sunday 17 Nov. 2019. The light blue line shows the traffic flow entering the West end of the system and the darker blue line shows the flow entering the East end. The red and orange lines in Fig. 2 illustrate the weekday traffic flow. The traffic flow on weekdays is from Monday 29 Oct. 2018. The orange line shows the traffic flow entering the West end of the system and the red line shows the flow entering the East end.

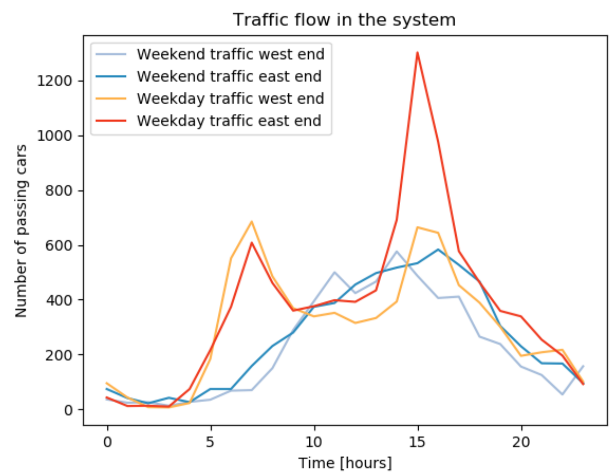

Fig. 2. Weekend and weekday traffic flow for the studied system

2) Temperature profiles: As mentioned in section II-B2, the driving efficiency is highly affected by the outside temperature. To integrate this into the FCS load model, 12 different temperature profile are used, i.e. one for each month. The temperature profile for each month was selected randomly, using weather data from Trondheim, Norway, and all temperature profiles are shown in Fig. 3.

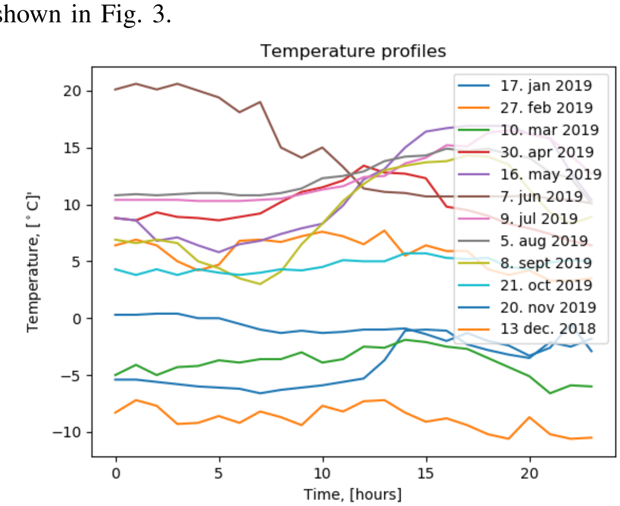

Fig. 3. Temperature profiles for Trondheim, Norway, used as stochastic input

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3) SOC of entering EVs: The SOC of the EVs when they enter the system is important for whether or not they will visit the FCS. According to a survey done by Electromobility Lab Norway [22], 90 % of EV owners predominantly charge at home. On average, the EV owners charge 4.4 times at home and 1.1 times at work each week. Based on the charging behavior and the traffic flow assumptions, weekdays and weekends will have different assumptions for the SOC_{arr} of the EVs. Table I shows the assumptions for the SOC of arriving EVs in the system during weekdays. It is assumed that EVs are mostly used for commuting, and that the majority of the EV owners do not have the possibility to charge at work during the day.

TABLE I
THE DISTRIBUTION OF SOC OF ARRIVING EVS TO THE SYSTEM THROUGHOUT A WEEKDAY.

Time	Alternative 1		Alternative 2	
	μ_{SOC} [%]	Prob	μ_{SOC} [%]	Prob
0-5	60	0.5	90	0.5
6-10	60	0.1	90	0.9
11-14	60	0.1	90	0.9
15-19	$SOC_{average(t=6,t=10)}$	0.8	90	0.2
20-23	$SOC_{average(t=15,t=19)}$	0.3	90	0.7

It is assumed that EVs drive fewer trips during the weekend, as they are not being used for commuting. Therefore, a constant SOC_{arr} of the EVs in the system is assumed throughout the day, with 90 % of the EVs entering with 90 % SOC and the remaining 10 % with 60 % SOC.

IV. RESULTS AND DISCUSSION

The input to the FCS load model is as shown in Table II. The two first parameters are given by the size of the actual FCS, which is two charging points both rated at 50 kW. The charging points have a lower power rating than the maximum charging power of some of the EVs in Table III. Therefore, these EVs will not be able to charge at their maximum power. The EV share in Trondheim is 10.8 % [24], as of June 2019.

TABLE II
THE INPUT TO COMPARE MODEL WITH ACTUAL DATA.

Deterministic input parameters	**Value**
Number of simulations	1 000
Number of charging points	2
Charging point power rating [kW]	50
EV share [%]	10.8
Stochastic input parameters	**Range**
Traffic flow	Weekdays, weekend
Temperature	January - December

The EV fleet used in the simulations is shown in Table III and is used to represent the current EV fleet in Norway. It is based on the 10 most common EVs in Norway as of 24 August 2019 [23][1].

[1]Both Tesla Model S, X and 3, and Renault Zoe are among the 10 most common EVs in Norway. The former are dropped due to Tesla having its own FCS network. Renault Zoe is dropped as it does not support charging above 22 kW.

TABLE III
BATTERY SIZE, MAXIMUM CHARGING POWER AND EFFICIENCY FOR THE 10 MOST COMMON EVS IN NORWAY

Model	**Battery [kWh]**	**Max charging power [kW]**	**Efficiency [kWh/km]**	**Share [%]**
Nissan Leaf	40,0	50	0.164	33
Volkswagen e-Golf	35,8	40	0.168	23
BMW i3	33,0	50	0.160	14
Kia Soul	42,0	50	0.171	10
Volkswagen Up!	18,7	40	0.168	5
Hyundai Ioniq	30,5	69	0.144	5
Nissan E-nv200	40,0	46	0.2	3
Mitsubishi I-miev	16,0	40	0.161	2
Jaguar I-pace	90,0	100	0.229	2
Audi E-tron	95,0	150	0.232	2

A. Comparison with real data

The results from the developed FCS load model are compared with real measurement data for daily energy demand and number of charging events from an actual FCS operated by Fortum. The data is from a randomly picked day. The data from the actual FCS is presented in Table IV. A total of 41 EVs charged at the FCS, resulting in a total energy demand of 357.7 kWh. This results in an average energy demand per charging event of 8.7 kWh. It is important to note that this is charging data for a random day and that there are many parameters that impact the number of charging events and energy demand of the FCS, such as temperature, day of the week etc.

To compare the results from the model with the actual FCS data, simulations are performed with input data from Table II. The total energy demand and number of charging events at the FCS were calculated for each simulation. The data is shown in Table IV. The charging data from the actual FCS is well in between the simulated 95 % confidence interval for both energy demand and charging events. The average energy demand per charging was 14.5 kWh. This is higher than in the real data. This could imply that some EVs are partially charging at the FCS and not charging until 80 % SOC, as assumed in the charging model.

TABLE IV
REAL-WORLD AND SIMULATED CHARGING DATA

	Real data	**Simulated data**	
		Mean	**95% CI**
Number of Charging events	41	20.7	7 - 45
Energy demand [kWh]	357,7	299.0	89 - 661

B. Load profiles

As mentioned earlier, the daily aggregated load profile of the FCS is a result from running the FCS load model. In Fig. 4, the red curve depicts the load profile for the FCS for a random day, the orange line is the average load for the same day, and the blue curve is the average load profile for the FCS for all of the simulated days. Nineteen EVs arrive at the FCS on this random day, and the FCS load reaches its maximum limit of 111 kW at one instance during this day. The peak-to-average power ratio (PAPR) is in this paper defined as the ratio between peak power and average power. The PAPR for the FCS for the random day is 11, with a maximum power of

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111 kW and an average power of 10 kW. A high PAPR is not ideal from the perspective of the distribution system operator (DSO), since it implies a high variance in the load from the FCS. Similarly, from the perspective of the FCS operator, low usage of the energy capacity at the grid connection of the FCS will result in high operating costs (e.g. grid tariff). Thus, a high PAPR would reduce the socioeconomic profitability of the FCS.

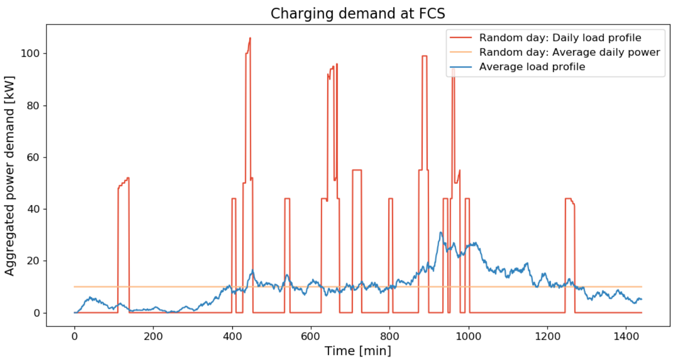

Fig. 4. Aggregated load profile for the FCS for a random day and the average FCS load profile for the 1000 simulations performed.

V. Conclusion and Further work

In this paper, a method for modeling a detailed aggregated load profile of a fast charging station for electric vehicles has been proposed. The proposed modeling approach includes traffic flow, EV charging curves and temperature-dependent EV efficiency. The input parameters for the developed FCS load model were the same as the specifications for an actual FCS, and the simulated results have been compared with real data. The comparison showed promising results, but more data is needed to further analyze the performance. The average charging demand per EV was higher for the simulated results than the real data. One reason for this could be that all EVs in the model charge to 80 % state of charge. Due to the high availability of home chargers, EVs may only partially charge at the FCS, and then complete the charging session at home. Partial charging will therefore be implemented in future work. The developed load profile for the FCS has a high peak-to-average power ratio, which reduces the socioeconomic profitability of the FCS. The proposed FCS load model is versatile, with the ability to change the number of charging points and rated power of each charging point. The proposed framework is also applicable for other electric vehicles, such as semi-trailers. Other future work could be to analyze the grid impacts of the FCS load profile and improve the mobility model to account for a more complex traffic flow.

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