Heavy-duty electric vehicle charging profile generation method for grid impact analysis

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***Abstract*—The transport sector is responsible for 20 % of the global CO_2 emissions. By transitioning from internal-combustion engine to battery-electric vehicles, there is a big potential in reducing the emissions. The upcoming heavy-duty electric vehicles (HDEVs) are expected to have a charging power between 100-1600 kW. A transition to HDEVs can cause challenges to the power grid to deliver the charging power needed. In this paper, a methodology to model the load profile of a high-power charging station for HDEVs is proposed. Generated load profiles with different future shares of HDEVs are used to study the impact on the power grid in a representative area in Norway. The loading of the regional substation exceeds its rated capacity when the share of HDEV is 25%, and its thermal limit when the share is increased to 50%. Extending the mandatory breaks for the drivers, and a corresponding reduction of the charging power, shows promising results.**

***Index Terms*—Electric vehicles, High-power charging, Load modelling, Demand profile, Grid planning, Heavy-Duty Vehicles**

I. Introduction

To cope with the 2° Celsius limit in the Paris agreement, new energy technologies must be included. The transport sector is responsible for 20 % of the CO_2 emissions worldwide. Road transport is the most significant contributor, with 75 % of the emissions from the sector. The second highest contributor to emissions in the road transport segment is road freight. It is accounting for 29.4 % of the total emissions in the transport sector. Half of this share is from heavy-duty vehicles (HDVs) [1]. By changing from classical internal combustion engines (ICE) to fuel-cell or battery-electric vehicles (BEVs), there is a significant potential in reducing the emissions.

An introduction of heavy-duty electric vehicles (HDEVs) will create a demand for new charging infrastructure in addition to the infrastructure meant for other types of electric vehicles (EVs), such as electric cars. The upcoming HDEVs are expected to have batteries in the size of 200-1000 kWh and a charging power ranging between 100-1600 kW [2], [3]. Thus, a transition to HDEVs can cause significant challenges to the power grid to deliver the charging power needed. In this paper, a methodology for generating aggregated load profiles for high-power charging stations (HPCS) for HDEVs is presented. The generated load profiles is then used to investigate the future grid impact on a power grid in a representative area along a highway in Norway.

A. Relevant literature

1) Load modelling: There have been conducted few studies on load modelling of high-power charging stations for HDEVs. However, the main principles are the same for load modelling of HPCS for electric cars. Two different methods are mainly used in literature to build the load model. An agent-based approach is used in [4], where each agent is operating autonomously according to one or several given objectives. Charging specifications, mobility pattern and vehicle type are defined for each agent. In [3], an agent-based model, which is originally developed for electric cars in [5], is used to generate load profiles for HDEVs, by changing the input parameters. A second and more common method is to build the model on stochastic parameters without the autonomous decision-making and interactions between the agents. References [6] and [7] are using Poisson processes with a predefined arrival rate or historical traffic flow data directly. The initial state of charge (SOC) is drawn from various probability distributions in [6]–[8]. In [9], SOC is not used as a parameter. Instead, data from HPCSs in Norway and Sweden containing charging duration is used. Monte Carlo simulations are often applied to evaluate the uncertainty of the stochastic parameters [3], [6], [7].

2) Grid impact: The authors in [3] have performed an analysis of the grid impact of HPCS for HDEVs. To look at vehicles with high enough charging power and battery capacity, HDEVs were defined as vehicles with a driving range of 400-800 km in a single charge. The investigated system had a HPCS with five charging points, à 1.2 MW, integrated. Time series analysis was used to investigate the grid impact. The analysis was conducted with the HPCS placed on different locations based on how suitable the connection point was. At the nodal location where there is sufficient capacity, the voltage never dropped below 0.95 p.u. At the nodal location where there is no sufficient capacity, the voltage dropped below 0.8 p.u.

Other literature focuses mainly on the impact of integrating charging of light-duty EVs or HDEVs with shorter driving range, such as urban electric buses. In [10], the impact of

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electric buses has been analysed. The mobility model is based on a bus network in Vienna, Austria. During operational hours, buses are charged for a few seconds at every station or for several minutes at the end-stations of a bus line. The charging power is ranging between 300 and 600 kW. The results implied that most European cities should be capable of integrating lines with electrical buses.

In [11]–[13], the impact from charging EVs with a peak demand ranging from 0.7 to 2.5 MW is investigated. The main finding is that the voltages at times suffer from flickering. However, the voltage drop rarely causes any severe problem. In [12], a load profile with a peak demand of 2.2 MW is applied on a 34-node test feeder. The voltage deviation in the worst-case scenario is observed to be 6 %. The load profile implemented in [13] has a peak demand of 2.5 MW. Initially, the highest loading of the transformer is 80 %. After the addition of an EV HPCS, the maximum loading is raised to 90 %. The voltage at the weakest point in the power grid dropped from 0.95 to 0.93 p.u.

B. Contributions

The main contributions this paper presents are:

- A methodology for generating aggregated load for an HPCS for HDEVs.
- Creation of charging profiles for a real traffic flow using the proposed methodology.
- Grid impact analysis on a power grid inspired by a real power grid topology.

C. Outline

This paper is divided into five sections. Following the introduction in Section I, Section II presents the methodology for generating load profiles for HDEVs and a description of power grid model development. In Section III the investigated system and cases are described. The results from the simulations are presented and discussed in Section IV. Section V concludes and presents the main findings from the research conducted in this paper.

II. Methodology

A. Load profiles for heavy-duty electric vehicles

To generate load profiles for an HPCS for HDEVs, a method for modelling the aggregated load of the HPCS is developed. The proposed method is based on the work performed in [7] which uses a stochastic approach for passenger EVs. Due to less known specifications of HDEVs and their behaviour compared to state-of-the-art electric cars, some simplifications have been made.

1) Simplifications: An unlimited amount of charging points is assumed at the HPCS. Thus, this model does not take vehicle queuing into account. This is done to highlight the possible total power demand in an area, i.e., the worst-case scenario that the network operator must be prepared for. Every heavy-duty vehicle (HDV) driver needs to have a mandatory break of 45 minutes after every 4.5 hours of driving time [14]. Thus, a charging duration is lasting until the battery is fully charged or when the break is over. In this paper, HDEVs are defined as electric trucks with a battery size in the range of 475-1000 kWh and a driving range of 400-800 km in a single charge.

2) Generating traffic flow: The arrival time for each HDEV is decided by using a Poisson process. It is assumed that each HDEV is independent of each other and that the expected number of HDEVs is kept constant in each hour as per the given traffic flow data. However, the expected number of HDEVs entering the system each hour varies throughout the day. Thus, a new Poisson process is conducted for each hour of the day, with different expected values.

Due to no information about the arrival rate of HDEVs, the expected value λ_h for each hour, h, is calculated from the real traffic flow q_h of HDVs and the desired $HDEVshare$, (1).

$$\lambda_h = HDEV\,share * q_h \tag{1}$$

The time between each HDEV arriving the HPCS, in minutes, is calculated with (2) as described in [7], where u is a variable that is uniformly distributed between 0 and 1.

$$w = -\frac{60}{\lambda_h} * ln(1-u) \tag{2}$$

The arrival time of the n^{th} vehicle is given by (3).

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

When the arrival time t_n is greater than or equal to 60 minutes, the Poisson process is finished, and a new process is started with the expected value for the next hour.

3) Generating HDEV objects: After the arrival time for each HDEV has been decided, the HDEVs profile will be created by applying their parameters to generate charging demand profile. Each HDEV is assigned parameter values based on the selected model type. The HDEV model type is drawn from a cumulative distribution function where the probability for choosing each model is equal. The input parameters are battery size, charging power and the probability of selecting a specific HDEV model.

When the HDEV is generated, it is given the initial SOC level when it arrives the HPCS, as $SOC_{arrival}$. The SOC value is drawn from a normal distribution with a standard deviation [15] equal to 0.1. The expected SOC value $\mu_{arrival}$ is decided by the battery size of the HDEV and the average energy used to travel to the HPCS, (4).

$$\mu_{arrival} = 1 - \frac{E_{travel}}{E_{battery}} \tag{4}$$

It is assumed that every HDEV starts the trip fully charged. The battery size, $E_{battery}$, is given for each model. The general energy demand for travelling to the HPCS, E_{travel}, is set by using SINTEF's energy module [16]. The energy module estimates how much energy different vehicle types use for a specific driving route in Norway.

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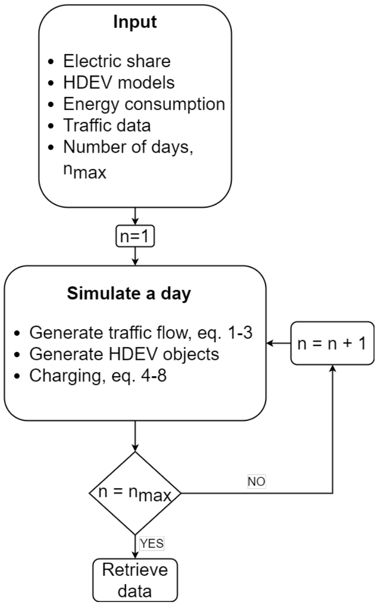

Fig. 1. Flow chart of the proposed method for generating aggregated load for an HPCS for HDEVs.

4) Charging: The amount of delivered energy to the HDEV in each time step, $E_{charged,t}$ is found by using (5), where P is the charging power (W) and Δt is the length of the time step. In this paper, the time resolution is one minute. Thus, the charging must be scaled from hours to minutes.

$$E_{charged,t} = P\Delta t * \frac{1}{60} \tag{5}$$

The maximum SOC level is in this paper set to 95 %, thus the maximum charged energy, E_{max}, is found from (6).

$$E_{max} = (0.95 - SOC_{arrival}) * E_{battery} \tag{6}$$

The HDEV will either charge until the charging session has lasted as long as the mandatory break, T_{break}, (7) or when the maximum charged energy is reached (8).

$$t = T_{break} \tag{7}$$

$$E_{charged} = E_{max} \tag{8}$$

Due to the stochastic parameters, the day is simulated 1001 times to get a representative set of the load profiles. Each load profile is then sorted by the mean energy demand for a time step to find the median load profile. It is chosen to run 1001 simulations to easily find the median profile in the set. A flow chart of the method is presented in Fig. 1.

B. Grid model

A representative power grid is created to observe the impact of HDEV charging. The power grid is created using the open-source package 'pandapower' in Python to conduct AC power flow analysis using the Newton-Raphson method [17]. The grid representation is created by assembling 'pandapower'

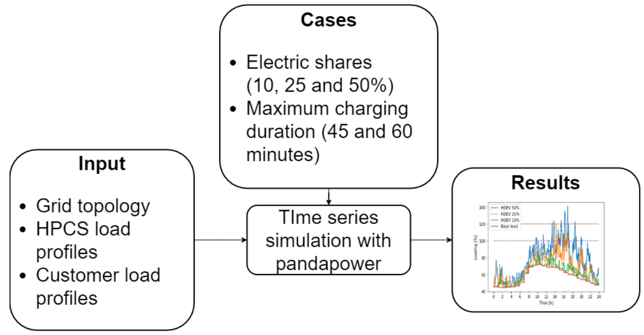

Fig. 2. Overview of the case study.

objects. By using the built-in Timeseries module in 'pandapower', it is possible to iterate through time steps. Thus, load profiles generated from the proposed load modelling method can be applied. The loads in the power grid are divided into two different types, base load and HPCS loads. The base load is created by dividing the surroundings into zones with each node having the aggregated load from the existing customers within that zone. The aggregated loads are made by combining demands from e.g., households, farms and schools, using general profiles created in the earlier research by SINTEF Energy Research [18]. In addition, HPCS loads for electric cars and HDEVs are included. The load profiles for electric cars that charges from HPCS are made by using the method presented in [7], while the HDEV charging demand is made using the method presented in this paper.

III. Case study

A real-life case study has been conducted on a small village in Eastern Norway, where 90 % of all HDVs driving between Oslo and Trondheim are passing by. The selected location is an established and designated lay-by area for HDVs, and refreshment point for drivers. The substation has its highest loading during the winter, thus the simulations are based on winter conditions to challenge the power system the most.

In this paper, the grid impact due to two different parameters, namely electric share and maximum charging duration, have been investigated. Simulations with three different electric shares, (10 %, 25 % and 50 %), of HDVs are conducted to observe the effect on the grid with potential electric shares in the future. The introduction of HDEVs may introduce high demand peaks. To reduce the demand peaks a possible charging strategy is applied. By extending the mandatory break from 45 to 60 minutes it is possible to reduce the charging power and still deliver the energy needed for charging the vehicle. An overview of the grid impact study for the different cases are presented in Fig. 2.

A. Traffic flow

The traffic flow is based on historical data recorded by the The Norwegian Public Roads Administration [19]. The traffic data is filtered to only include vehicles with a length greater than 12.5 meters. The traffic flow passing by the HPCS is presented in Fig. 3.

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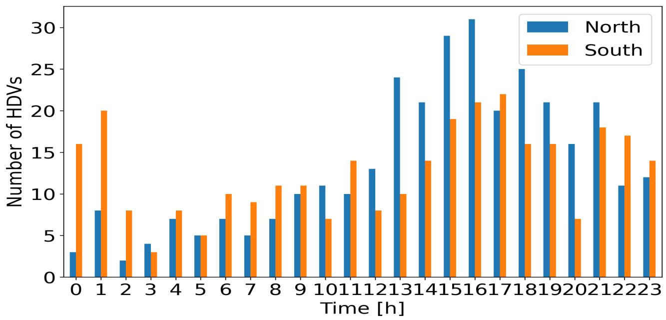

Fig. 3. Hourly measured traffic flow of HDVs, divided in driving directions north and south.

TABLE I
DISTANCE, ENERGY AND DRIVING EFFICIENCY USED BETWEEN THE STARTING POINT AND THE HPCS.

Starting point	Distance [km]	Energy [kWh]	Driving efficiency [kWh/km]
Oslo	291	414	1.42
Trondheim	172	256	1.49

B. State of charge

In addition to arrival time, the SOC of the visiting HDEV has a great impact on the load profile of the HPCS. It is assumed that all HDEVs are starting at Oslo or Trondheim. The energy demand from driving to the HPCS from Oslo and Trondheim is found in Table I. The proposed driving efficiency of the Tesla is 1.25 kWh/km [20], which is slightly lower than the generated values from the energy module. Due to the winter conditions that are assumed in this model, the driving efficiency will likely be worse than the proposed values from Tesla. Thus, the values from the energy module are used as an expected value for the energy demand.

C. HDEV models

To the best of the authors knowledge, there is no HDEVs operating at this route today. To make a representative HDEV fleet, the upcoming Tesla Semi and Freightliner eCascadia are considered. Both models are long haul vehicles with an expected driving range of at least 400 km in a single charge. The Tesla Semi is also chosen as they already have received orders from Norway. In addition, the two HDEV models showcase two different scales of future HDEVs. Tesla Semi has a battery size and charging power over double the size of the Freightliner eCascadia. In table II the input parameters for each model are presented. The charging power of the Tesla Semi is scaled down from 1.6 MW to 1.333 MW to appreciate the charging power variations during the charging session.

D. Power system topology

The grid model is based on a grid topology located in the county called Innlandet in Eastern Norway. It contains 13 buses that are connected to the regional grid via a 66/22 kV substation transformer. Bus 0-10 is the existing topology and the aggregated customer loads. Bus 11 and 12 represent two

TABLE II
INPUT PARAMETERS FOR THE HDEVS TO THE LOAD MODEL

HDEV model	Battery size [kWh]	Charging power [kW]
Tesla Semi	1000	1333
Freightliner eCascadia	475	400

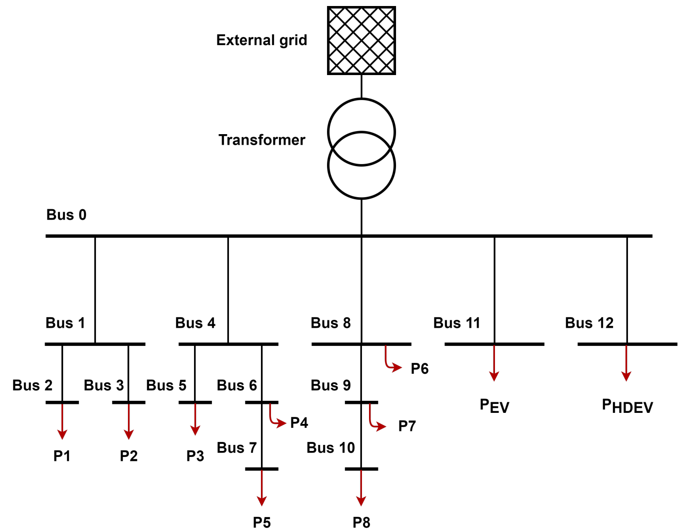

Fig. 4. Single line diagram for the grid model.

HPCS, one for electric cars and one for HDEVs. It is assumed that both are connected directly to the transformer. The single-line diagram is presented in Fig. 4.

At the located area there are several HPCSs. To model the load profile, these HPCSs are combined and modelled as a single HPCS with 20 charging points. Sixteen outlets having a capacity of 150 kW and four with 350 kW. The representation of the EV fleet is made by choosing the ten most registered EV models in Norway [21]. The load profile for the HPCS for HDEVs is created with parameters as described in Section III.

IV. RESULTS AND DISCUSSION

A. Load profiles

The generated load profiles, with a one-minute time resolution, in Fig. 5 shows that charging of HDEVs introduces demands with major changes in the load demand. They represent the median profile of each case. When the electric share is 10 %, the demand is evenly distributed through the day and the peaks are rarely above 4 MW. In the cases where the electric share is increased to 25 % and 50 % there are greater variations in the load. The peak demand are mainly around 9 MW and 13 MW respectively. These peaks are quite high compared to HPCS for electric cars. To generate peaks in the sizes of 13 MW it is needed 85 outlets à 150 kW operating at full capacity. Thus, the load impact from HDEVs is significant compared to EVs. It is important to note that the method used in this paper assumes that all charging demand is served. This is done to observe a worst-case day for the DSO. The results

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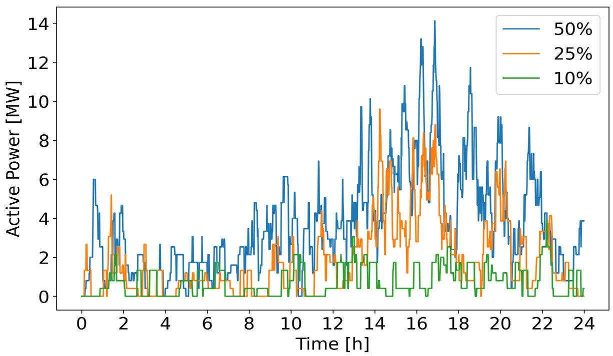

Fig. 5. The resulting median load profiles from the simulations with electric shares of 10 %, 25 % and 50 %.

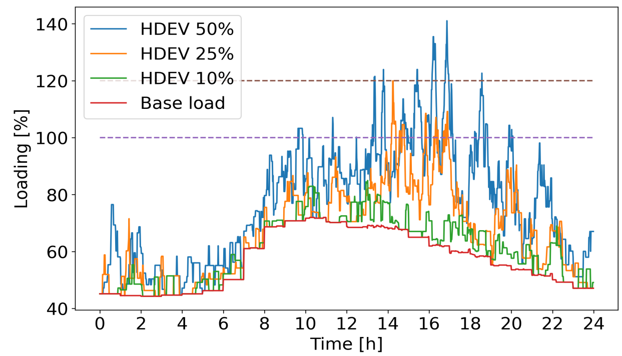

Fig. 7. Transformer loading for the base load and HPCS loads with electric shares of 10 %, 25 % and 50 %.

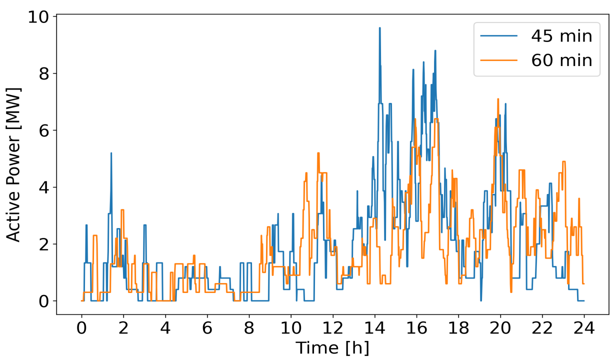

Fig. 6. The resulting median load profiles from the simulations with 25 % electric share. Shown with both 45 and 60 minutes mandatory break.

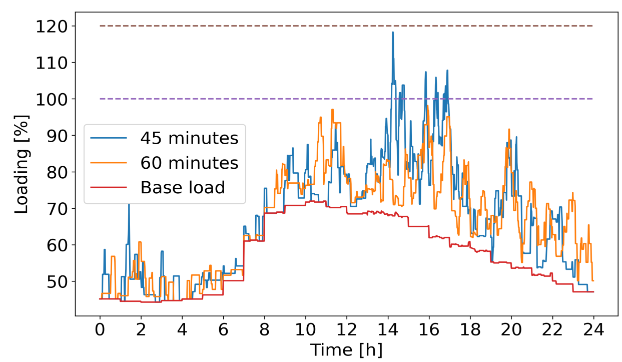

Fig. 8. Transformer loading for the base load and HPCS load with electric share of 25 %. Shown with both 45 and 60 minutes mandatory break.

are thus potentially overestimating the demand in some cases.

One potential way to reduce the peaks is to extend the mandatory breaks for the drivers, which allows lowering the charging power. The resulting median load profiles for the ”25 % case” are presented in Fig. 6. By extending the maximum charging duration from 45 to 60 minutes, the highest peaks were reduced with approximately 2 MW. Consequently, the load demand throughout the day has less difference in the values at the peaks and valleys, which causes a more predictable load.

B. *Grid impact*

The generated load profiles were further used in power flow analysis to investigate the impact on the local substation transformer and the voltage quality. From the simulations, it is evident that the loading from the HDEV HPCS makes a significant impact on the transformer loading, presented Fig. 7. In the ”25% case”, the rated capacity is exceeded in certain time steps in the interval between 14 and 17. The exceeding peaks never reach the theoretical thermal limit at 120 %, which allows the transformer to still operate as long it is for short periods only. When the electric share is further increased to 50 %, the overloading increase both in time and magnitude, causing the transformer to exceed its thermal limit.

To minimise the operating time with overload in the ”25 % case”, the load profiles with extended charging duration were applied. By extending the charging duration to 60 minutes, the operating time with overload is removed, seen in Fig. 8. It is still possible to experience overload as the presented results are using the median profile.

The majority of the base load is connected to bus 9 and 10 and is the buses with the lowest voltages. Fig. 9 presents the voltages when there is only the base load in the system, and when the electric share of HDVs is 25 % and 50 %. It is evident that the introduction of HDEVs causes great fluctuations in the voltages. In the ”25 % case”, the largest voltage drop occurs around 14, when the voltages decrease with 0.01 p.u. The number of events when the voltage decreases with at least 0.01 has increased in the ”50 % case”. At 17, the voltage drops approximately 0.02 p.u.

V. Conclusion and Further work

This paper has presented a methodology for modelling the aggregated load profile of an HPCS used by HDEVs. In the study, it is assumed that all the load demand from HDEVs is served to show a worst-case day for the DSO. The generated load profiles were further used in a grid impact study of a representative area in Eastern Norway. The HPCS introduced a significant load to the system with peak values equal to 4 MW, 9 MW and 13 MW for three different HDEV shares,

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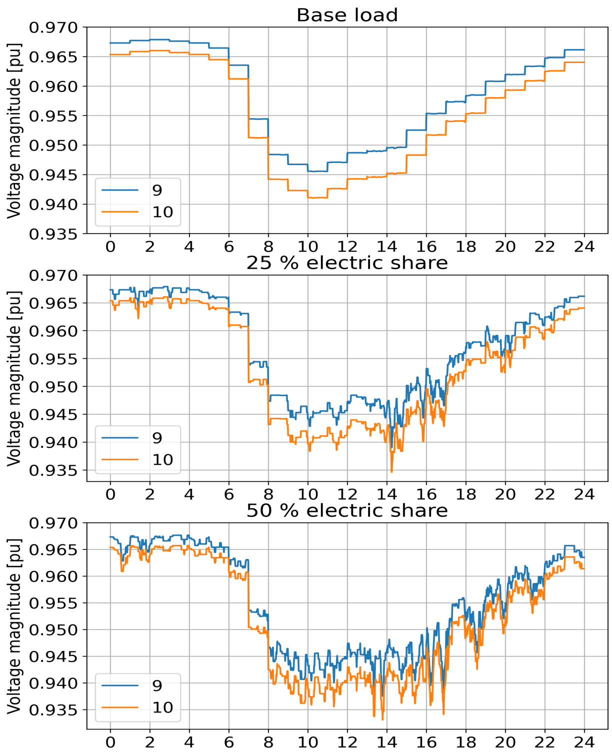

Fig. 9. Voltages at bus 9 and 10 with base load and different electric shares.

respectively (10 %, 25 % and 50 %). These loads caused the associated substation to exceed the rated capacity when the HDEV share was 25 % and exceed the thermal limit when the share was further increased to 50 %. A proposed strategy of extending the drivers' mandatory breaks from 45 to 60 minutes and lower the charging power correspondingly to maintain the same energy demand were applied. This resulted in a reduction in the peak load of the HPCS, and the substation to operate below rated capacity. The methodology may overestimate the load demand. Thus, a verification of the methodology will be conducted when validation data is available. This approach is fully dependent on the input parameters and a sensitivity analysis of the input parameters to discover potential errors in the generating data due to inaccuracies in the input should be investigated. To highlight a more realistic behaviour of the HDEVs, queuing will be implemented in the method in further work.

Acknowledgment

The authors gratefully acknowledge the Research Council of Norway and industry partners for the support in writing this paper under project 295133/E20 FuChar - Grid and Charging Infrastructure of the Future. The authors would also like to thank Elvia, a Norwegian DSO, for their contribution of grid data for this study.

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