Agent Based Modelling and Simulation of Plug-in Electric Vehicles Adoption in Norway

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***Abstract*—This paper looks into the consumption side of the power balance, and more specifically on the effects of utilizing an increasingly larger fleet of Plug-in electric vehicles (PEVs) for personal transportation. To asses this, an Agent Based Model of PEVs has been extended and developed with different charging strategies. The model simulates power demand from a given number of PEVs in a given area, and may be useful for policymakers and researchers alike. Simulations ran for the city of Trondheim reinforce the notion that the rising adoption of PEVs might not only pose a substantial challenge due to the relative size of the power demanded, but more critically also because of the variability that the charging profiles exhibit. On the other hand, the different behaviour of the PEV agents, as modelled through different charging strategies, indicate that incentives such as price signals might effect how much the agent charge at different times. Hence it may even lend the PEVs batteries as assets to help stabilize the power balance in the electric grid.**

***Index Terms*—Agent Based Modelling, Plug-in Electric Vehicles, Power Demand Variability**

I. Introduction

The transition to a more sustainable society and economy imposes a challenge for the power system due to raising variability in the system. It is induced by an increasing share of renewable energy sources on the supply side, and the growing adoption of Plug-in Electric Vehicles (PEVs) on the demand side. The focus of this paper is on the latter. The adoption of PEVs has seen a tremendous rise throughout the last decade, facilitated by batteries seeing a steady improvement for both cost and energy density [1]. As such, Norway poses an interesting case study, as the country is one of the greatest PEV adopters to date with PEVs at 3,7% of the total fleet and market share of new car sales above 15% [2]. Hence, it is increasingly crucial to understand how the rising adoption of PEVs will impact the energy system, especially from a Norwegian perspective. Publications from the Norwegian Water Resources and Energy Directorate (NVE), [3] and [4], shows how the PEV adoption will pose challenges especially for transformer stations, transmission lines and voltage quality in Norway. Yet, a challenge when analyzing the electricity consumption of PEVs is the complexity added by human decisions. However, one accredited method to analyze such complex, socio-technical systems[5] is that of Agent Based Modelling (ABM), from the field of Complexity Science.

There is abundant research done on understanding the challenges that arise as an increasing PEV fleet demand more energy, as well as modeling how flexible charging might aid the integration of PEVs to the power system. The reports of [1] and [6] gives a great overview and outlook on the adoption of PEVs. As for analyses based on real data and surveys, the paper of [7] is to recommend. It present information from the ”The EV Project” which gathered PEV driving and charging data in the US. In [8] it is discussed how the PEVs will impact the grid. For the Norwegian case, there are other studies to take note of, besides the two mentioned NVE reports.For instance, [9] discusses charging behaviour in Norway specifically, based on survey data from a few hundred PEV owners. There are also many papers who discusses how to smooth out PEV charging variability. Many of these presents optimization methods which may be used for peak shaving and valley filling. Examples of such are [10] who uses game theory and Nash equilibrium for decentralized charging, [11] who utilizes transition matrix for decentralized charging, [12] and [13] who are solving AC-OPF with Wind, Hydro Power and PEV scheduling, and [14] who gives an assessment of the need for flexibility for PEV integration in Norway.

As for work that has utilized the methodology of ABM in the context of Power Systems, the work of [15] offers a great introduction to the possibilities of AMBs for grid systems. Other important work is that of [16] and [17], which both utilizes the MATSim[18] ABM software to simulate PEV driving and charging behaviour. The former uses game theoretical perspectives to analyze competition for power and the benefits and possibilities with an aggregated PEV manager, the latter parking. Where these works are dependent on a much bigger model built for transport simulations in general, the work of [19] develops a custom-made ABM for PEVs driving and charging.

This paper looks into the effects of utilizing an increasingly larger fleet of Plug-in electric vehicles (PEVs) for personal transportation, by extending the fundamental ABM model of [19], analyzing different PEV behaviour and power system implications. None of the previous work has yet, in the authors opinion, fully utilized the most valuable feature of ABM - namely the possibility to analyze the uprising of extreme events from complex behaviour - to assess the key question of power demand variability. The charging behaviour of PEVs that we want to analyze, may due to human influence be characterized as Socio-technical systems. Hence the use of ABM is a well-suited method to cope with the complexities of our task. Through the implementation of an ABM mimicking the basic characteristics and interactions of the individual components of a PEV charging system, and the heterogeneous nature of an ABM, we should not only be able to simulate the PEV charging behaviour, but also observe the rise of seemingly unpredictable and complex patterns[20] in their power consumption. The paper is organized as follows; part II presents general information, assumptions and specific charging strategies, gathered information on how PEV charging behaviour, discusses how this may be utilized for an ABM, before defining rules for the agents to operate after based on the presented material. part III an overview of the model and the case of Trondheim, presents a brief overview of the implementation of the model, as well as the case study of Trondheim for which the model was further customized. part IV presents some of the main results from the simulation and analysis, of the Trondheim case study, and discusses the findings. part V discusses the findings, and part VI concludes the paper.

II. Agent Based Modelling of PEV Behaviour

A few empirical studies have been made that collects data from existing populations of eclectic vehicles, and analyze them to get a sense of their behaviour. In [7], they present the Fig. 1, showing that most EVs are charged once per day and start charging with 20-80% SOC.

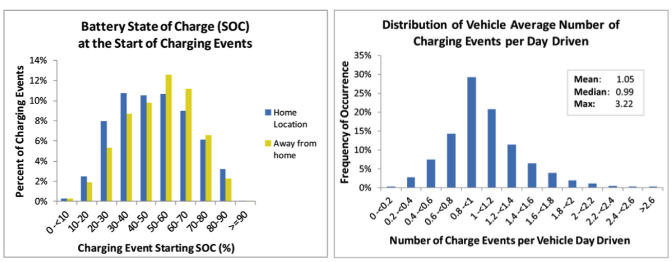

Fig. 1: Charging in terms of SOC and frequency. [7]

However, despite observable profile characteristics, the charging behaviour is still rather volatile, and can also change from different times of year and different locations [21]Contrasting the daily profiles presented in [4], with [21] and [8], it is clear that there are a lot of variation in the charging profiles across different regions.

Agent Based Models are generally bottom-up computational programs where the set of agents all have certain characteristics, and where one specifies certain interaction rules between them and also with the environment. To simulate the fundamental behaviour of the agents, we develop a few basic rules that allows the reproduction of the real observed phenomena and data. From this we may change the parameters, or add a new rule, to observe how it effects the system. It should be noted that by using an ABM one seeks insights on complex problems that is not possible to gain through explicit techniques. As a result, the mathematics here is by itself not very advanced.

To build an ABM of PEVs, we start by making similar assumptions as [19], namely that:

a) The charging of the agent vehicles happens either when they are at home, or at a charging station within a certain distance from their working place in the city.
b) For simplicity, we let the agents decide whether to start charging or not when they arrive either at home or at work. Thus, if they don't connect at first, they will wait until the next arrival at a charging station to charge.
c) Every agent has a home location and work location, which for the sake of simplicity is assigned randomly within some defined areas outside the city.
d) There is a chance that each agent has an errand after work.
e) Every agent has the possibility to charge its car at home.

With these ground rules we may begin building an ABM of PEV energy demand. It is of course possible to alter these assumptions, yet for instance assumption b) simplifies some of the details required to build a the model.

In addition, it is also important to define further the exact mechanism of how the agent decides to charge its car. We need to define a few charging strategies or charging behaviour that the agents should adhere to. The strategies are what will have the most impact on the results, and will give insights on how PEV agents may behave given certain conditions.

The charging strategies that are used in this work is presented below:

1. **"Dumb" charging:** The agents charge whenever they have the need and there is a free charging spot close by.
2. **Probabilistic charging based on SOC:** As seen in Fig. 1, most PEV owners charge when their battery has between 0,2-0,8 SOC. With this strategy the agents do not start charging as soon as they have the need. Instead they will charge according to a certain probability that becomes higher and higher the less power they have left on their battery. For the sake of simplicity, we hence assume a linear probability function, such that
$$Pr_{SOC}(SOC_t, SOC_{min}) = 1 - \frac{SOC_t - SOC_{min}}{SOC_{max} - SOC_{min}} \tag{1}$$
that is, the probability of charging, Pr_{SOC} at a given time instance with a corresponding SOC_t of agent n's battery is given by the difference to the desired minimum SOC_{min} scaled with the difference to the maximum $SOC_{max}(=1)$.
3. **Probabilistic charging strategy based on SOC and price:** Where the first two strategies allow for minimal interaction between the agents, the agents here take into account the price of electricity as well. The higher the price, the less likely they are to charge. This approach allows indirect communications through their response to the price, that here change according to power demanded.
The price in our model may for simplicity determined by how much of a specified maximal power capacity is used, in a linear fashion. More formally the price, $\pi(t)$ at time t is given as
$$\pi(t) = \pi_{min} + C \cdot \frac{\sum_{i=1}^{N(t)} P_i^{PEV}}{P_{max}} \tag{2}$$
where C is a scaling constant, N(t) is the number of connected vehicles at time step t, P_i^{EV} is the power charged by PEV i, and P_{max} is the maximum charging capacity of the power system. If $C = (\pi_{max} - \pi_{min})$, then π_{max} and π_{min} simply defines the range for the price.
We also add the assumption that all agents have available electricity at a given price at their homes, π_{home}, which is

higher than π_{min}. This reflect that many home owners in Norway don't buy their electricity on spot at their homes, but with monthly contracts. To develop a probability model based on price and SOC, we may start out with price alone. To make the probability 0.5 for $\pi_t = \pi_{home}$, we may use a function of the form

$$Pr_{price}(\pi_t) = \frac{1 + f_1(\pi_t)}{2} \tag{3}$$

where $f_1(\pi_{home}) = 0$. Moreover, if we let

$$f_1(\pi_t) = \frac{(\pi_{home} - \pi_t)^3}{(\pi_{home})^n} \tag{4}$$

where

$$n = \frac{3 \cdot \ln(\pi_{home} - \pi_{min})}{\ln(\pi_{home})} \tag{5}$$

A function describing likelihood to charge based on price to be 0 at highest price and 1 at lowest, and fairly flat at the middle, refer to Fig. 2, it will need to be of a polynomial with a higher than 2. Hence cubic power in the numerator of Eq.(4) is the easiest. we have a third order polynomial function where $Pr_{price}(\pi_{min}) = 1$, and hence $Pr_{price}(\pi_t = 2(\pi_{home} - \pi_{min})) = 0$. However, we also want the function to be less curved when $\pi_t > \pi_{home}$, which for instance may be invoked by multiplying $f_1(\pi_t)$ with

$$f_2(\pi_t) = \left(\frac{\pi_{max}}{\pi_t}\right)^m \tag{6}$$

where π_{max} is some maximum desired price to pay for power. Choosing $m = 5$ and updating n to

$$n = \frac{3 \cdot \ln(\pi_{home} - \pi_{min}) + 5(\ln(\pi_{max}) - \pi_{min})}{\ln(\pi_{home})} \tag{7}$$

we express the probability of charging according to price as

$$Pr_{price}(\pi_t) = \frac{1 + f_1(\pi_t) f_2(\pi_t)}{2} = \frac{1 + \frac{(\pi_{home} - \pi_t)^3}{(\pi_{home})^n}\left(\frac{\pi_{max}}{\pi_t}\right)^m}{2} \tag{8}$$

We multiply f_1 by f_2 to make the curve less curved above

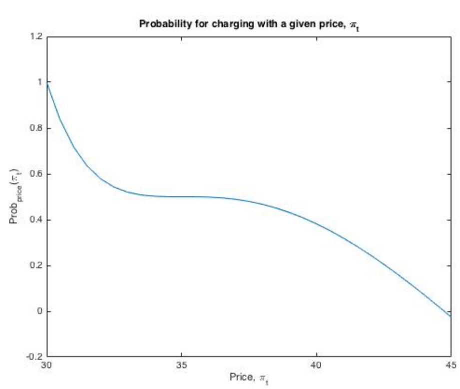

Fig. 2: Probability for charging based on price.

$\pi_t = \pi_{home}$. It means it is less important how much the electricity price is over home price, than how cheaper it is. This is to reflect that many agents will be eager to be at the margin, than to loose extra money if they really have to charge, see Fig. 2. To calculate the probability affected by both price and SOC, we multiply these together and multiply them by 2,

$$Pr_{SOC\&price}(\pi_t) = 2 \cdot Pr_{SOC}(\pi_t) \cdot Pr_{price}(\pi_t) \tag{9}$$

so that if they are both at their middle case (50% SOC and $\pi_t = \pi_{home}$), then the joint probability will still be 50% for charging.

III. Case: Implementing an ABM of PEVs for Trondheim

The simulation of the Agent Based Model has been implemented in JAVA, as it is a widely used object-oriented programming language. It facilitates the use of classes of objects that intact, a native part of ABM. It is also fairly straight forward to get to interact with Internet APIs.

To get a general impression of how the ABM, it is here presented a UML class diagram. The Fig. 3 shows the model architecture used. To get more information about the details of this particular ABM, see [19] for the underlying model, and [22] for the specifics of the model implemented here.

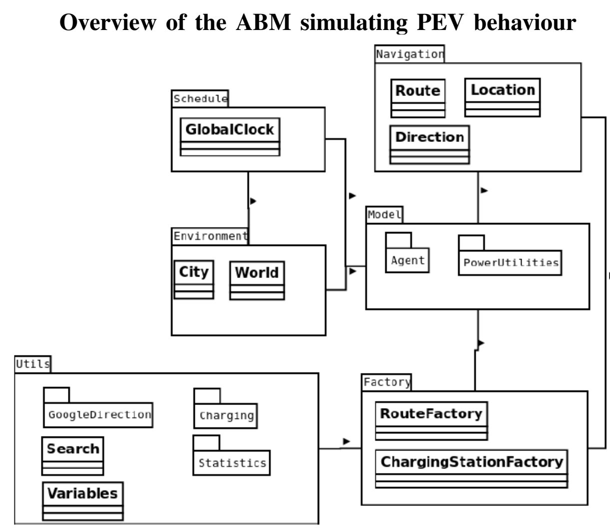

Fig. 3: Overview of high-level architecture of the agent based model[19].

The city of implementation in this model has been chosen to be Trondheim, the city of residence of the Norwegian University of Science and Technology (NTNU). The charging stations used in the model, as displayed in Fig. 4, are the ones actually excising in the city. An up-to-date list of stations and their characteristics may upon request be accessed from [23] and downloaded using their API. An API to Google Maps was also used to find the distance and time for all the agent's driving routes, laying the basis for all the energy consumption calculations.

At the heart of this model we have the PEV agents. To introduce some diversity to the electric vehicle agents, it is possible to include many types of cars, as well as different agent characteristics (eg. different working times) etc, to make the model more realistic or reach a desired level of detail. Therefore a few different types of cars implemented as specific types of electric vehicles for a certain agent, such as Tesla

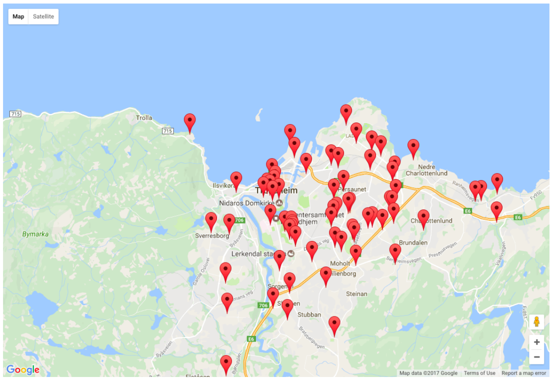

Fig. 4: Map of charging stations in Trondheim as of 12.06.2017.

Model S, Volkswagen eGolf and Nissan Leaf as can be seen in table I. For this simulation each agent has a probability of 1/3 to have each of the cars.

Brand Model	Nissan Leaf	Tesla Model S	Volkswagen E-Golf
Consumption Rate [kWh/km]	0,174	0,198	0,179
Charge Rate [kW]	6,6	10	7,2
Battery size [kWh]	30	100	24

TABLE I: Variety of cars implemented in simulation, data from [24] and [25]

IV. Results from the Case

This section presents results from the simulations of the ABM for the city Trondheim. It also presents the observed variation in simulation data for two of the cases, and at the end prognosis for PEV power demand in the future based on this model.

A. *Daily profiles of total demand and SOC for the ABM with different charging strategies*

After implementing the ABM in Java with different strategies, a number of different simulation runs was conducted, from which to compare the four different strategies. The simulation runs were each done with 1500 agents over 10 days, with the maximum power of the grid set to 4500kW in most cases. One should also keep in mind that all simulations are based on several random realizations, and such one could run even more iterations to get better insights in the results.

1) Dumb charging: Fig. 5 depicts the total demanded power by both home and public chargers from the grid with the dumb charging strategy. The graph shows that the charging has a characteristic pattern, with larger amount of charging in the evening at the home stations, indicating there are too few chargers in the city. In Fig. 6 we see how the State of Charge (SOC) of the battery of 100 out of the 1500 agents during a 10-day period. We may observe that the agents, by design, charge as soon as they have the opportunity, maintaining their battery level close to maximum.

2) Probabilistic charging strategy based on SOC: Fig. 7 depicts the total demanded power from the grid. Again, it shows that the power used for charging is almost twice as much power from the home-stations compared to the city ones. However, we observe that the graph has a more gradual increase and decrease.Fig. 8 shows how 100 of the 1500 agents store energy in their batteries during the simulation. As can be

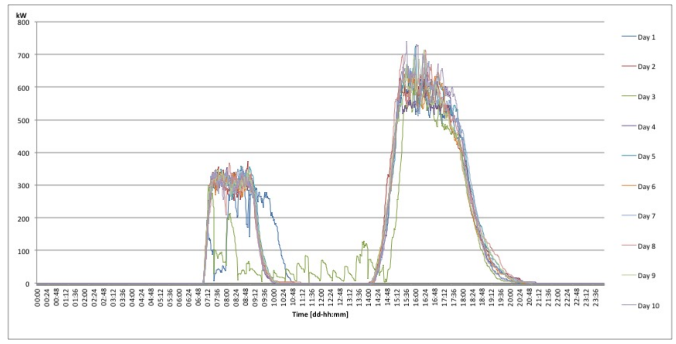

Fig. 5: Total power demand from 1500 EVs during 10 days with dumb charging

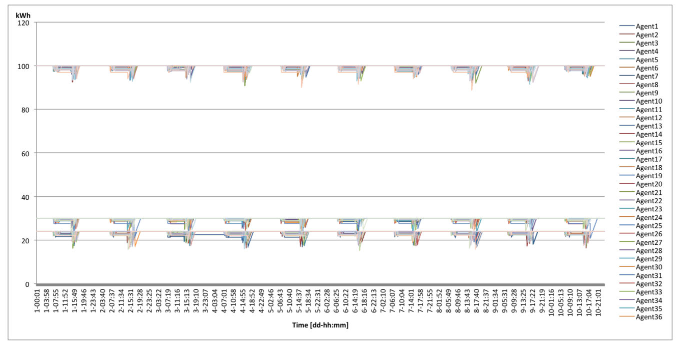

Fig. 6: SOC during 10 days for 100 to 1500 EVs with dumb charging

observed from the graph, this strategy clearly makes it more probable that the agents wait a while before charging their batteries. However, it does not seem to generate a almost even distribution around 80%-20% of SOC, as in Fig. 1.

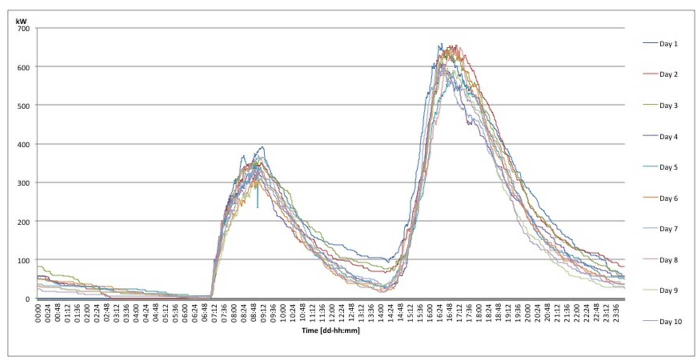

Fig. 7: Total power demand from 1500 EVs during 10 days with charging strategy based on SOC

Fig. 9 shows the power demand from the different charging stations. Notably, charging station with ID: 0 with the highest peak, corresponds to the agents charging at their homes. Two of the other stations with quite high peaks are the stations of ID: 1309 and ID: 66, corresponding to the largest charging stations at Sirkus Shopping Mall and IKEA in Trondheim with 10 and 12 charging spots respectively.

3) Probabilistic charging strategy based on SOC and price: The graph in Fig. 10 shows the total demanded power from the grid when the maximum desired power level is set to 4500 kW. We here observe that the graph shows some of the main characteristics of the previous cases, just more smoothed out,

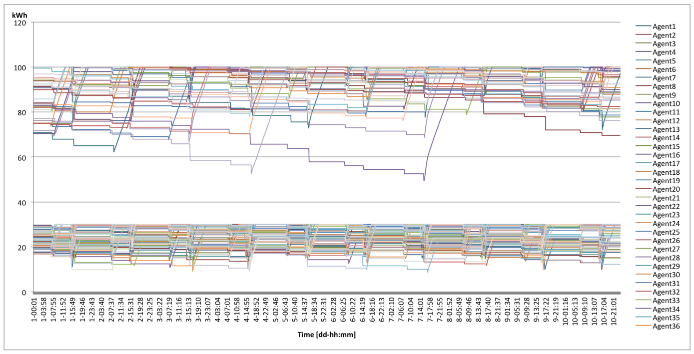

Fig. 8: SOC during 10 days for 100 ot 1500 EVs with charging strategy based on SOC

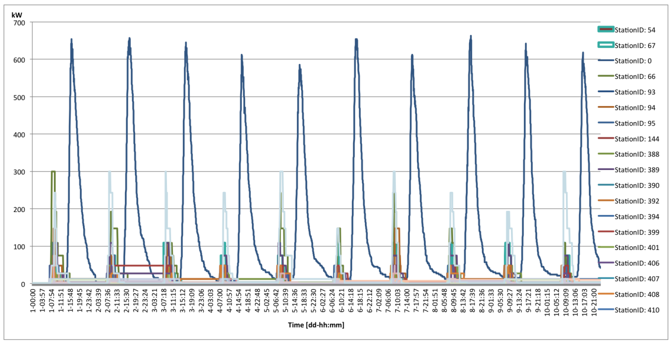

Fig. 9: Power demand per station during 10 days of 1500 EVs with charging strategy based on SOC

and with pikes in the first period due to more complex agent indirect interaction.

The results shown here, is not to emphasise that smoothing is possible through different charging strategies, but rather to assess the short-term variation and volatility that is present in scenarios with different charging strategies.

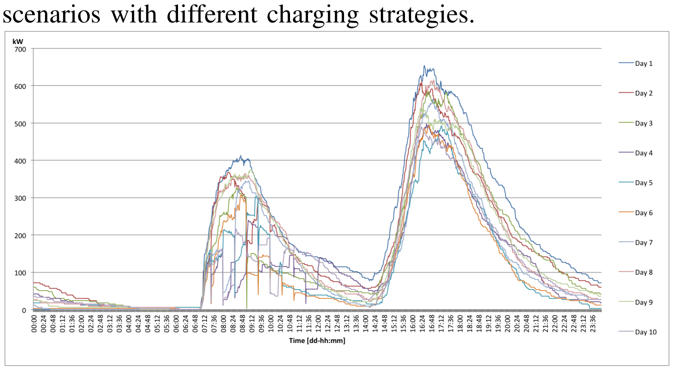

Fig. 10: Total power demand from 1500 EVs during 10 days with charging strategy based on SOC and price and P_{max}=4500 kW

B. Variability in simulated scenarios

In Figs. 11 and 12 we may observe the profiles of the runs simulation 40 days with 1500 agents. In the former the agents utilize the 2nd strategy, that is charging based solely on SOC, whereas in the latter the agents are influenced by both their SOC and the energy price with a P_{max} = 1500kW. A feature with these graphs is that they present the average, 5%, 25%, 75% and 95% percentiles for the data in the same minute for the 40 days. Hence, we may better observe the variability within the data. From the Figs. we can see it is clear that there is a considerable variability band especially in Fig. 11 representing the SOC scaled charging strategy.

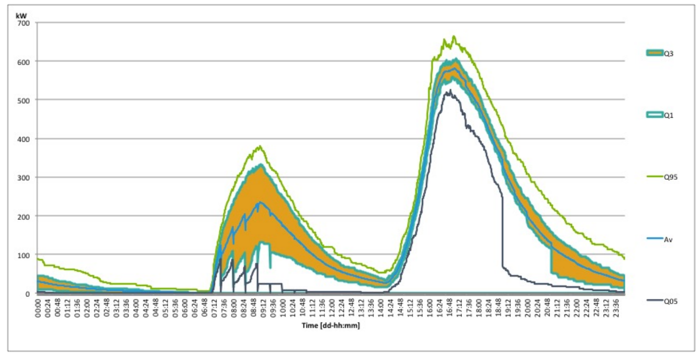

Fig. 11: Total power demand from 1500 EVs during 40 days with charging based on SOC

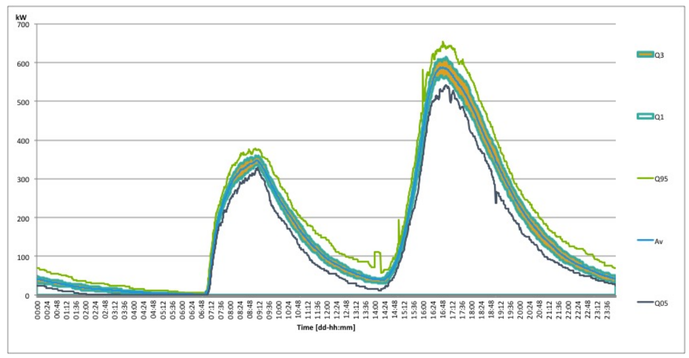

Fig. 12: Total power demand from 1500 EVs during 40 days with charging strategy based on SOC and price and P_{max}=1500 kW

Additionally, the same statistics was computed for the whole aggregated time series over all the 40 days. The results are presented, along with the standard deviation (SD) in table II. From table II, we see that the maximal value of power demanded is about the same, however the average value seems to be higher in the latter case. However, contrary to what the graphs seem to display, we also see that the standard deviation, a measure of variability in a time series, is slightly higher in the latter case as well. However, the standard deviation on relative changes is high in the second, but astonishing in the first.

TABLE II: Statistics for 40 day simulation statistics with 1500 agents with different charging strategies

Stats [/kW]	Q95	Avg	Q05	SD	SD of prof.av.
SOC	522	137	0	163	38,66
SOC&Price, 1500P_{max}	537	161	3	167	17,88

C. Prognosis of power demand

With the reports of [3] and [4] from NVE, and data from Statistics Norway (SSB), we surmise make a prognosis for PEV adoption, as presented in table III.

Data for Norway	2015	2030	2050
Inhabitants	5 100 000	5 900 000	6 300 000
Personal vehicles	2 600 000	2 900 000	3 300 000
Electric vehicles	73 000	1 500 000	3 300 000
Power to EVs [TWh]	0,2	4	7,9

TABLE III: Prognosis of Population, Cars and EVs in Norway, (NVE)

One thing that stands out from this table, is the amount of energy demanded from the electrical vehicles is expected

TABLE IV: Projections of vehicle fleet and power demand [kW]

Base case	Vs in Nor.	PEVs Tr.hm.	Avg dmnd	Q95 dmnd
2030	2 900 000	61 921	6 147	22 106
2050	3 300 000	131 481	13 052	46 939
Today's rate	**Vs in Nor.**	**PEVs Tr.hm.**	**Avg dmnd**	**Q95 dmnd**
2030	2 900 000	111 539	11 073	39 820
2050	3 300 000	131 999	13 104	47 124
Lower rate	**Vs in Nor.**	**PEVs Tr.hm.**	**Avg dmnd**	**Q95 dmnd**
2030	2 900 000	39 496	3 921	14 100
2050	3 300 000	98 204	9 749	35 059

only to be 4 TWh in 2030 and a maximum of 7,9 TWh in 2050. Compared to the total amount of energy of 43 TWh that went to transportation using personal vehicles in 2015 (see [26]), that reduction is quite substantial. The lowered energy consumption from transportation will be thanks to the efficiency gain of not having to convert energy to another energy carrier than electricity.

Another analysis conducted was to compare the results of the data insight from the last section IV-B, with the outlook presented in table III.To do this, we first had to make projections for the adaption of PEVs in Norway, and then make some scenarios based on this. One alternative here is to use a System dynamic approach. A simple System Dynamic model was implemented in VENSIM[27]. However, the tuning of the parameters in the model did not yield realistic enough results. Instead we use an S-curve, or logistic function,

constructing a base case based on the prognosis of NVE presented in Table III, a high case which uses the growth rate of the last couple of years as the starting point of its S-curve, and a low case where we assume full electrification will not happen.

To make the projected adoption cases relevant to our model, we assume that the PEV adoption in Trondheim scales similarly. Hence, based on the fact that in 2016 SSB accounts a total 4190 PEVs in Trondheim in 2016, and the NVE prognosis for vehicle adoption displayed in table III, we may scale the average statistical data from table II and make a prognosis for power demand in Trondheim due to PEV, presented in table IV

From table IV we see that there is quickly a high demanded power from the PEVs, reaching above 10 MW already in 2030 in all cases. However, if one compares these results with the energy consumption calculation of NVE from table III, we find that the number presented in the projections of table IV are a little low. Indeed, if one multiplies the number of PEVs in each scenario with an average driving distance of 12 300 km/year (assuming it will be the same as the 2015 statistics from SSB) and an average energy consumption of 0,2 kWh/km for the PEVs, we find that the base case in 2030 should have had an average power demand of 17 389 kW and similarly 36 923 kW for 2050.

The lower value of energy demand from out model may be well explained by the fact that we only simulate driving to and from work and errands on weekdays, and do not include transportation back and forth to cabins for instance in weekdays and holidays. However, our bottom-up model seems to do a fairly good job in predicting the power demand within a reasonable range of the top down calculation.

Comparing the figures of 17 389 kW and 36 923 kW to the total energy consumption of about 3,5 TWh in Trondheim yearly, see [28], corresponding to an average of 400 MW per hour, the power demand is about 4% and 9%, in 2030 and 2050 respectively, of average demanded power in Trondheim, or 6% and 13% of average electricity demand.

Hence, a substantial electrification of the car fleet will demand a significant amount of available power from the grid. If we take this trail of though further and scale the Q95 results also, it seems probable that the grid in Trondheim also has to supply a peak power demand that will be about 22% and 43% of average power demand from electricity.

V. Discussion

The ABM built in this project allows for a few more in depth insights as well. Since this model was simulated using real data for Trondheim, the analysis provides take-aways for policy makers in this city.

Firstly, regarding the spatial distribution of charging demand. The amount of charging stations installed in the city center of Trondheim is somewhat limited forcing many of the agents to charge at home instead. Yet, this is not really a consumer problem, since most cars are more that capable of riding back and forth to job and charge at home. What might be a problem, is that the distribution grid of areas outside the city might not be dimensioned for having many PEVs charging simultaneously. Coupling this with the fact that the average chairing power for home charging is assumed to rise from an average of 3,1 kW today to 5,6 kW [3] with full electrification, we see that there might be even greater issues with the grid in home areas in the skirts of the city.

A key question from the introduction was the magnitude of power demand. Whereas the model and simulations here give an average demand of power of about 6 MW in 2030 and 13 in 2050, the revised numbers shows us a electric power demand of about 6% and 13% and peaks routinely be about 22% and 43%. If one is to take account for extreme charging event after holidays which again is not captured in these simulations, the maximum charging demand would be even greater. In any case this would be a challenge for the grid to handle if it happens uncontrollably, and some mechanisms will be needed to guide or incentivise when the PEVs should charge.

The other main inquiry we wanted to make was on the variability as the personal transportation system develops to an electrified one. From the general charging profiles, we see that there are not only considerable peak-to-trough variations intraday at in these simulations. Moreover, one specific charging profile may also vary considerable from the average profile, and the minute to minute variations are also substantial. However, due to the nature of the model with only weekdays in consideration, the coincidence of these simulations is at most about 20%. Again, with more extreme cases eg after weekends, the absolute variability may be even higher if more cars are charging at the same time.

Coupling the findings mentioned above, of substantial spatial and temporal variability and a rinsing magnitude of demand, it is clear that the power grid may face challenges when serving a ever growing number of PEVs. However, the models also show that price signals might work in order to incentivise PEV owners to charge at times more beneficial to the power system. Moreover, a even more connected system, both in terms of energy and information through the rise of Smart Grids, might enhance the possibly to achieve peak-shaving and valley-filling.

VI. Conclusion

To conclude, we have developed an PEV fleet model that captures the uncertainty and complexity of agents with different probability scenarios and then tested it on a real case-study which is city of Trondheim with existing public charging stations. it seems clear that the rising adoption of PEVs pose a challenge due to both the relative size of the power demanded but also the variability that the charging profiles exhibit. On the other hand, the different agent, or PEV owner, behaviour, as modelled through different charging strategies, indicate that incentives such as price signals might effect how much the agent charge at different times. As such, a development towards Smart Grid might even lend the PEVs as assets to help stabilize the power balance.

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