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Long term individual load forecast under different electrical vehicles uptake scenarios

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Abstract

More and more households are purchasing electric vehicles (EVs), and this will continue as we move towards a low carbon future. There are various projections as to the rate of EV uptake, but all predict an increase over the next ten years. Charging these EVs will produce one of the biggest loads on the low voltage network. To manage the network, we must not only take into account the number of EVs taken up, but where on the network they are charging, and at what time. To simulate the impact on the network from high, medium and low EV uptake (as outlined by the UK government), we present an agent-based model. We initialise the model to assign an EV to a household based on either random distribution or social influences - that is, a neighbour of an EV owner is more likely to also purchase an EV. Additionally, we examine the effect of peak behaviour on the network when charging is at day-time, night-time, or a mix of both. The model is implemented on a neighbourhood in south-east England using smart meter data (half hourly electricity readings) and real life charging patterns from an EV trial. Our results indicate that social influence can increase the peak demand on a local level (street or feeder), meaning that medium EV uptake can create higher peak demand than currently expected.

Keywords: Low Carbon Technologies, Long Term Forecasts, Agent Based Modelling, Low Voltage Networks

1. Introduction

Long term forecasting of future peak load demand is vital for the efficient and secure operation of power systems. In order to implement the use of more sustainable energy generation and to continue providing quality service to their customers, distributed networks operators (DNOs), and other organisations involved in the energy sector, employ decision support mechanisms. The expected increased uptake of low carbon technologies (LCTs), such as electric vehicles (EVs), photovoltaics, combined heat and power and heat pumps will subsequently lead to new demands and possibly increased strain on the network. Long term forecasts predicting load demand several years into the future ([1]

considered up to 8 to 15 years) provide valuable decision support for developing future generation and distribution planning.

One of the aims of our work is to understand the long-term impact of EVs on low voltage (LV) networks, more precisely on the LV peak load. Not only may LCT, in particular EVs, uptake rates vary but it is likely that uptake will be clustered on the same LV networks due to similar demographics (similar people live down similar streets), and social influence factors such as "keeping up with the Joneses". In order to model long term individual loads influenced by EVs under different uptake scenarios, we adopt an agent based modelling approach. Use of agent based modelling for load forecasting purposes is a relatively novel approach, but it is increasingly popular in this field. Agent based modeling approach has previously been adopted for implementing large-scale simulation tools for electricity wholesale markets and power system analysis such as electricity market complex adaptive system (EMCAS) [2], [3] and agent-based modeling of electricity systems (AMES) [4] software. The most commonly adopted definition of an agent by Wooldridge and Jennings [5] specifies a set of properties that must characterize an entity to effectively define it an agent such as autonomy (a certain degree of control over its own state), social ability (the capability to communicate and collaborate on a task), reactivity (the possibility to perceive the context in which they operate and react to it appropriately) and pro-activeness (the possibility to take the initiative, starting some activity according to internal goals). In [6] and [7] the authors define an agent-based simulation as "a collection of heterogeneous, intelligent and interacting agents, which operate and exist in an environment, which in turn is made up of agents". Agents are usually adaptive and goal-oriented [8]. To generate forecasts, we use data from smart meters collected as part of the Thames Valley Vision (TVV) project[1]. Our results from three real subnetworks demonstrate that the combination of agent-based modelling, LV simulation and the real data collected comprises a useful methodological approach to forecasting long term electric load demand, taking into account the factors such as temporal and spatial characteristics of adoption of renewables (e.g. EV). The result is a flexible computational environment that enables simulating and comparing various future energy scenarios. This model is sustainable as it allows new features to be added when household data becomes available. Additionally, the model can be scaled up to the substation level when the data set is large.

2. Previous work

Modelling complex systems, especially ones that include human behaviour such as energy demand and generation, raise significant challenges based on the complex interactions between different parts of the system, lack of knowledge of governing mechanisms and the limited predictability of human behaviour.

[1] http://www.thamesvalleyvision.co.uk

Overall, two approaches dominate: a top-down approach that captures global characteristics of a system and aims to find analytic solutions often assuming the homogeneity of individuals by ignoring the local, individual level and a bottom-up approach that explicitly models global as well as local characteristics of a system. There are two major model categories based on top-down approach and used for electricity markets : Input-Output (I/O) models and Computable General Equilibrium Models (CGE) [9]. As classified by Ventosa et al. [10] optimisation models, equilibrium models and simulation models are the most significant models based on bottom-up approach. Further we discuss in detail one of the main types of simulation models - agent based models.

2.1. Agent Based Models in Energy

Agent based modelling (ABM) is a bottom-up approach which uses a computer simulation to track the model through time and/or space. In Hellbing and Ballietti [11] principles are given for creating agent based models. Starting from the evidence that one wants to explain by the model, one should first decide on the "big picture", data or observations that need to be reproduced by the model. Also the purpose of the model/simulation should be stated - are we after an insight, an extrapolation or a prediction? What are the agents? Sometimes we don't need to model every single individual - groups of people may represent one agent. When we decide on our agents, one needs to formulate hypotheses about mechanisms that lead to system behaviour that need to be reproduced or explained. One should refrain from model assumptions of the behaviours which need to be reproduced or explained, i.e. the rules that are in the model should be simpler than the mechanism that we wish to explain. Finally, the validation of the model on different levels should be executed unselectively stating which features were reproduced and which were not. ABM provides more realistic ways to implement learning effects in repeated interactions [10]. The outputs of ABM may not be optimal but they are the results of the emergent interactions between agents. Agent based models can show "what could be" under different scenarios across uncertain futures whereas optimisation and equilibrium models show "what should be" [12], [13]. Within the last ten years ABM has been widely adopted for electricity market research. Two of the most prominent ABMs in this sector are EMCAS [2], [3] and AMES [4]. Veneman et al. consider EMCAS the mostly viable ABM due to the validation efforts performed on the model. In particular EMCAS has been used in the analysis of plug-in-hybrids and their effects on the transmission grid [14].

Also ABMs can be used for exploring different scenarios of long term individual energy load. The main advantages are that a model can comprise many heterogeneous components that could interact between themselves and nonlinear dynamics could be captured [15]. Additionally, ABM structure would allow for inclusion of many different scenarios into the same model. A detailed reviews of current offer of ABM models that can be used to analyse the integration of distributed generation in energy systems are given in [16] and [12]. Weidlich et al. in their critical survey of agent based wholesale electricity market models acknowledge ABM approach and simulation of the electricity market to be effective. The authors also identify current ABM methodology problems in agent learning behavior, market dynamics and complexity, calibration and validation as well as model description and publication that need to be considered for the further development in this sector. We foresee the model validation as a main challenge due to the long-term time scale but this is not a problem exclusive to ABMs. Acknowledging that there is a compromise between model tractability and the simplicity of agents' behaviour and interaction rules we try to keep the model as simple as possible.

2.2. Electrical Vehicles impact on distribution networks

Electric vehicles (EVs) are the promising future direction in the automotive industry's development to replace a significant amount of gasoline vehicles to provide energy-saving, CO2 free and environmentally friendly cars [17], [18]. A range of models have been developed in the energy sector for forecasting and for looking into the integration of renewable technologies in energy systems. Connolly et al. [19] provides a review of over 30 different models (including EMCAS [2] ABM mentioned in the preceding subsection) that can be used to analyze the integration of renewable energy sources.

Studies of the potential impact of EVs on the distribution network level have been conducted starting from as early as the 1980s [20], [21]. More recent studies focus on EV impacts on efficiency and performance of distributed networks, as well as EV charging control problems by investigating different scenarios such as unrestricted charging, peak and off-peak charging, diversified charging, and charging at varying power levels [22], [23], [24], [25], [26]. The study in Clement-Nyns et al. [27] obtained results with the quadratic programming technique showing that coordinated charging of plug-in hybrid electric vehicles can lower power losses and voltage deviations by flattening out peak power.

Recent trends show increased interest in the use of vehicles as distribution storage units [28], [29].Despite these potential benefits, as EVs begin to penetrate the vehicle market they can potentially lead to undesirable impacts on distribution networks due to the increased demand from EV charging patterns. With charge rates expected to increase in the next generation of models they would be among the largest loads in distribution networks with the potential to increase peak demand, provoke large voltage drops and have a negative effect on networks overall performance [30], [18]. A few case studies were conducted over the last decade that conclude uncontrolled EV charging could lead to significant increases in peak demand, power losses and voltage problems [31], [23]. Galus et al. [24] in their study introduce a method, which integrates ABM simulations for analysing the impacts of wide-scale Plug-In Hybrid Electric Vehicle (PHEV) integration in the electricity grid of Zurich. In [24] the authors find that uncontrolled vehicle recharging can lead to overloads on multiple voltage levels, and that uncontrolled charging increases the overall system peak load and changes the system load curve.

De Hoog et al. [30] focus on exploring the impact of electric vehicles on voltage stability, and the results show that location and phase allocations of the

EVs in network have a very significant impact on network stability. However not only locations of the EVs can have an impact on network stability but also electricity tariffs. Salah et al. [25] in their work using ABM methodology give estimates of the impact of EV charging behavior on the transformer substations. Furthermore they come to a conclusion that under flat electricity tariffs and high EV penetration levels around a number of substations will be overloaded, thus further EV charging coordination is required.

In [18] the authors showed that based on their simulation results, uncoordinated charging of EVs increases peaks and active power loss on the power grid, which is caused by the charging load of EVs. So the EVs charging or discharging control must be introduced with the increasing number of EVs. Considering the constraints of powergrid operation and battery function, the authors proposed an optimal power flow based EV charging and discharging strategy to improve the performance in distribution networks. Another study on controlling EVs charging and discharging was conducted by Dusparic et al [32]. The authors propose a multi-agent reinforcement learning approach that uses load forecasting for residential demand response. EVs are controlled by reinforcement learning agents and given necessary data to evaluate how they can be influenced to charge the battery and keep transformer load under a designated maximum load by shifting their charging from high load to low load periods. The results of simulations in [32] show that agents learn to shift neighbourhood demand to the off-peak periods based on providing current load information and load prediction for the next 24 hours.

2.3. Social influence

The rate of diffusion of new products and services being adopted through the different strata of society is a big topic in marketing research, but it is also relevant in other fields such as network analysis, epidemiology and sociology. [33]. Ryan and Gross's study from 1943 [34], investigating the adoption of hybrid seed corn in Iowa farms, is among the earliest results showing that social factors play a bigger role than economic ones in the adoption of new technologies. One of the classical models is Bass's s-curve model [35], the growth model assuming that the probability of an adoption in any moment is linearly dependent on the number of previous adoptions. This results in adoptions having exponential growth to a peak followed by exponential decay.

In a recent review, [36] the authors affirmed that modelling diffusion processes became increasingly complex. This was the result of several forces at work - incorporating spatial diffusion; challenging the monotonicity assumption of the uptake curve and focusing on turning points and irregularities in the uptake; considering partially connected and small-world networks between individuals instead of the assumption of full connectivity, or ignoring existing networks' structure; using individual level modelling instead of aggregated models, and so on. While we see the importance of taking into account all the different aspects of social influence, there is not always data available for the calibration of models, and also the models might become intractable.

Another widely used classical model is a threshold model [37]. In the threshold model, individuals are connected through an observed social network (it can have an arbitrary structure). Each individual is assigned a personal threshold and will adopt an innovation in time t only if enough (i.e. more than the individual's threshold) of her/his neighbours already adopted previously. Different models, the so-called cascade models [38], assign probabilities to links between vertices - each active vertex v could activate its neighbour w with probability $p_{v,w}$. In [39] it was shown that generalised versions of those two types of models, threshold and cascade, are equivalent. In our work we used a revision of cascade model with fitness function.

Being able to predict which customers are more likely to adopt an EV in the future can help DNOs to identify potential network areas that would be affected the most. A number of studies were conducted in USA aiming to analyse the characteristics based on both EV owners and non-EV owners demographic survey data. Initial findings suggest that, apart from social influence factors such as "keeping up with the Joneses", higher income and presence of photovoltaics (PV) can have an impact on who purchases (e.g. based on demographic data in USA around 41% of PV owners have an EV) [40], [41].

2.3.1. Our contribution

We developed an agent-based simulation to explore the influence of electrical vehicles on the low voltage network. Our primary concern was 10 year forecast of individual electrical load, and patterns of individual behaviour that contribute to shifts of peaks or to the creation of local networks with new peaks. We used for our simulations three UK governmental scenarios for the uptake of low carbon technologies in UK in the next decades, and the real data of individual household's half-hourly load, and of daily charging patterns obtained from an electrical vehicles trial. We used a slightly modified cascade model to model social influence of neighbours to the adoption of a EV which resulted in a clustered neighbourhoods uptake. We compared how random and clustered uptake differ under three scenarios on three real-life local neighbourhood suburban networks. Our main findings show that the peak demands for the clustered distributions in comparison with the results for random distributions are higher for high and medium uptakes. This is due to people influencing each other in clustered distribution mode, and it is related to the ratio of uptake versus the influence factor. For the first four years our results show similar peaks and midday peak times on Christmas day for both random and clustered distributions, which leads us to the conclusion that demand for these years is driven by general behaviour and not by EV charging behaviour. We also explored altering household EV charging behaviour in the next 10 years on a half-hourly basis, and our results show that for ordinary days peak loads and peak times are dependant on EV charging patterns as expected. However on special days such as Christmas day our results for randomising EV charging patterns show that peak loads and corresponding times are mainly influenced by the base load consumption (electricity usage before EV charging). These findings can be useful for DNOs long-term planning and maintenance.

3. Long-term forecast model

As our main concern is an individual electrical load, we consider a household to be an agent - the irreducible part of a system. We would like to be able to predict an agent behaviour in future 8-10 years on half-hourly basis, and to aggregate agents behaviours on street/feeder and substation/neighbourhood levels. Calibrating a model with data, assigning simple constraints/rules to households, and using a computer simulation, we track the model through a number of future years.

The agent based model we implemented comprises of 'household' agents with fixed coordinates corresponding to the map of the substation (see Fig.1) provided by SSEPD (Scottish and Southern Energy Power Distribution). Currently our agent based model is static i.e. the agents do not change location and do not interact but do observe each other. The model changes with every time step (1 year) and records the change of load demand for every agent. The distribution of electrical vehicles between agents is implemented to be random or clustered. In a clustered distribution, the agents influence each other through observing neighbours' previous behaviour. The strength of this influence can be varied by the user.

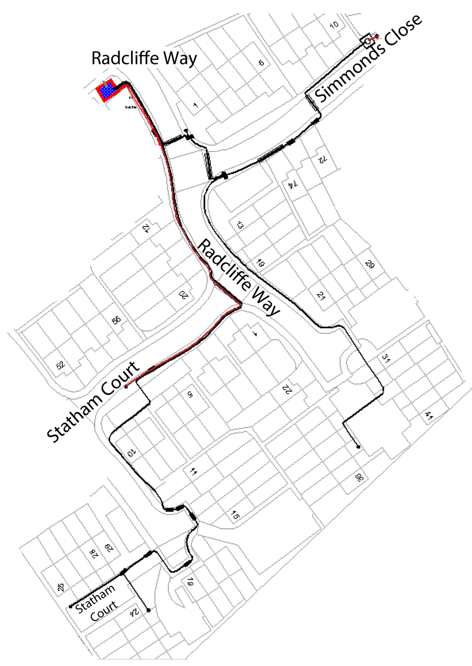


Figure 1: Radcliffe substation map

The uptake of EVs is modelled according to four future energy scenarios (Department of Energy and Climate Change (DECC) works-stream 3) [42] which propose different rates of adoption for different global future trends (see Table

1). EVs are distributed between agents and the change of load demand for every agent is recorded. In our model the experiments are implemented for 3 scenarios (DECC works-stream scenarios 1, 3 and 4 on slow and fast-charged EVs uptake).

DECC Scenario	No	EVs Uptake
Medium - High abatement in low carbon heat	1	48%
Medium - High abatement in transport and bio-energy	2	48%
High - Focus on high electrification	3	67%
Low - Purchase of international Energy	4	31%

Table 1: DECC work stream scenarios on slow and fast-charged EVs uptake

The scenarios are devised for several types of low carbon technologies, but as we are concentrating on EVs only, we use low, medium and high scenario, omitting scenario [2] from 1 since it is identical to scenario [3] for EVs. Figure 2 plots the total number of EVs for the households (total of 75) included on the substation diagram per year in high, medium and low EV uptake scenarios correspondingly.

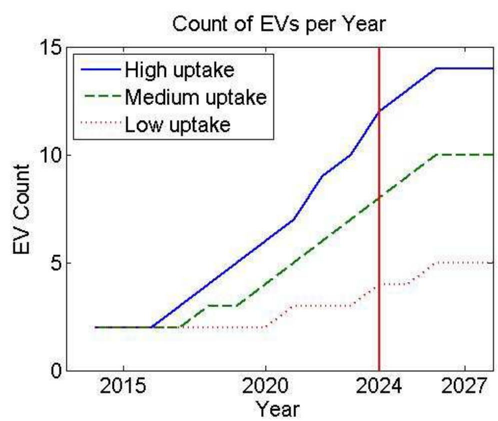


Figure 2: Total number of EVs for 75 households

The more detailed description of the long term forecasting ABM, including the rules and constraints set, is given below. Figure 3 illustrates the setup of agent Household. The agent Household is initialised with a real-life load profile. If it obtains EV, its charging will be added to its profile. The list of its neighbours is obtained from a low voltage substation diagram.

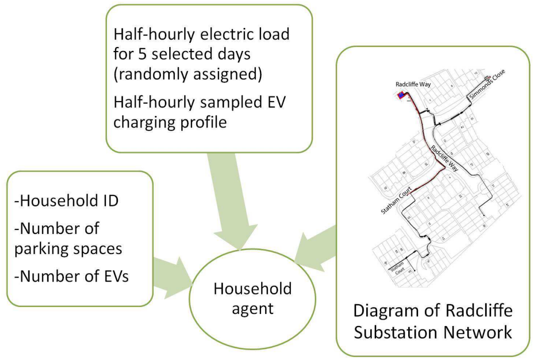


Figure 3: Initialisation of agent Household

When a particular scenario (high, medium of low uptake of EVs) is chosen, this defines the number of EVs that will be distributed in the neighbourhood each year. If Random Distribution is then chosen, EVs will be distributed uniformly at random to the eligible households, i.e. ones that have enough parking space and that do not own already 2 vehicles; if Clustered distribution is chosen, EVs will be distributed to the eligible households using so called Roulette Wheel or fitness proportionate selection method where fitness will depend on the number of neighbours already owning EV (see Figure 4).

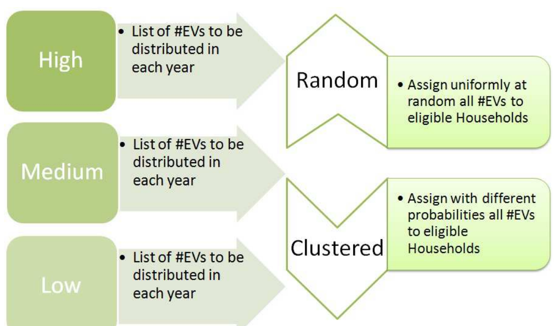
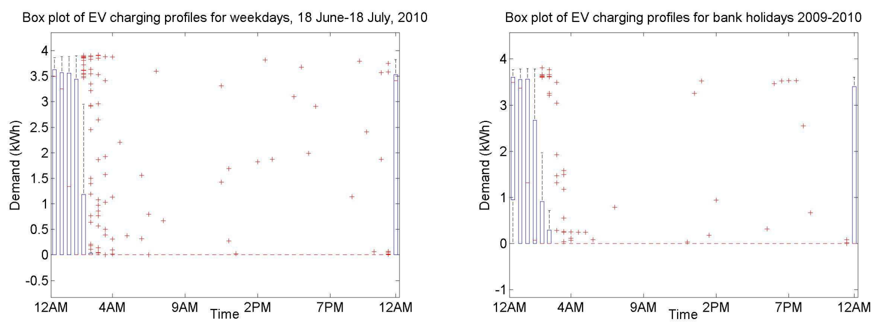


Figure 4: Distribution of EVs for 3 scenarios

As we are modelling the south-east of England suburban areas, and our households are domestic, we imposed a limit of two EVs per household. We have chosen 5 random days for our experiments, two in the middle of summer, two in the middle of winter and one Bank Holiday (Monday, August 9, 2013; Wednesday, August 14, 2013; Wednesday, December 25, 2013; Tuesday, January 7, 2014; Saturday, January 18, 2014) in order to have a good representation across the heavy and light demand seasons respectively. We are looking at extremes since troughs and peaks are among DNOs' main concerns. We take into consideration slow and fast-charged EVs as we have national level predictors and real data charging patterns for cars with chargers up to 7kw.

3.1. EV charging profiles

For EV charging profiles we use a data-set gathered by SSEPD as part of its research into electric vehicles which contains 19 EVs' charging profiles at half hourly resolution from 2009 until 2010. We select from a sample of charging patterns for each day of the week during one month in summer, one month in winter and bank holidays. Figures 5a and 5b graphically depicts this data for weekdays in June-July 2010 period and Bank holidays in years 2009-2010 correspondingly through its quartiles. Since according to the trial's data the customers were encouraged to charge overnight, we observe that almost all of the data is concentrated around 12am.



(a) Weekdays, 18 June - 18 July, 2010

(b) Bank holidays 2009-2010

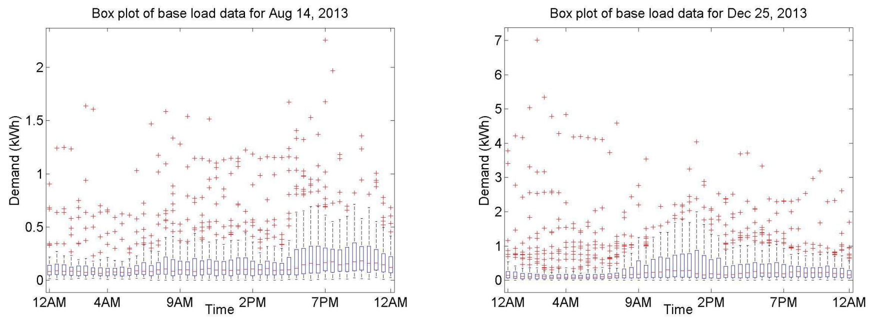
Figure 5: Box plots for EV charging profiles

3.2. Base load profiles

We use historical load consumption data from smart meters collected as part of the Thames Valley Vision (TVV) project[2] in Bracknell area. This data collected at half hourly resolution is sampled for 75 households for previously chosen 5 days (Monday, August 9, 2013; Wednesday, August 14, 2013; Wednesday, December 25, 2013; Tuesday, January 7, 2014; Saturday, January 18, 2014). Figures 6a and 6b graphically depicts this data for August 14, 2013 and December 25, 2013 correspondingly through its quartiles.

Further we generate average load profiles from base load data. In the Figure 6 we plot mean load consumption of base load data for Aug 14, 2013 and Dec 25, 2013 since these two days are referred to in further section to demonstrate our main results. For August 14 (Figure 7a) we observe peak demand 0.2781kwh occurring at 7pm and maximum relative standard deviation is 1.1352. Similarly for December 25 (Figure 7b) we obtain mean peak demand 0.5469 kwh occurring at 1pm and maximum relative standard deviation is 1.423. Similarly for Figure

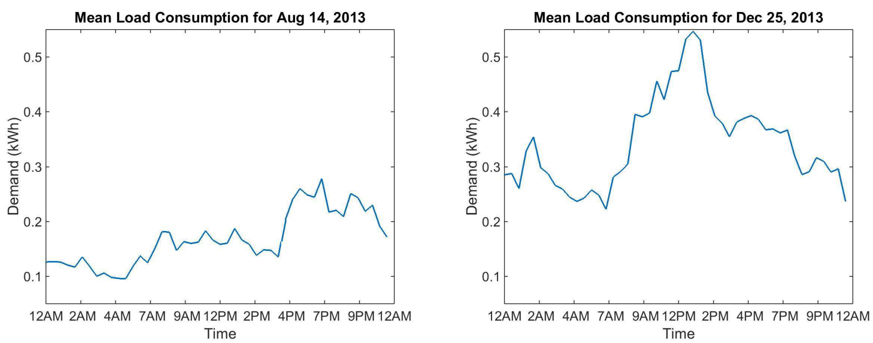
[2]http://www.thamesvalleyvision.co.uk



(a) Wednesday August 14 2013

(b) Wednesday December 25 2013

Figure 6: Box plots for base load data for Aug 14 and Dec 25, 2013



(a) Wednesday August 14 2013

(b) Wednesday December 25 2013

Figure 7: Mean base load consumption for Aug 14 and Dec 25, 2013

we observe peak demand 0.2781kwh occurring at 7pm and maximum relative standard deviation is 1.1352.

3.3. Initialising Long Term Forecasting Model

The model is implemented in Java using open source Repast agent-based simulation libraries [43], which enable separation between model specification, model execution, model visualisation, and data storage. The following sequence of steps describes how our long term forecasting simulation engine works.

```
Data: Number of Households, Base load profiles, EV charging profiles,
      Diagram of local subnetwork, Number of EVs for each year under
      3 scenarios
Result: HH updated profiles
Create list of neighbours N(H) for each household H from the diagram ;
Randomly assign load profiles to Households;
for  Year = 1 : 10 do
    Read #EVs to be distributed in Year according to chosen scenario;
    if Random then
        Assign uniformly at random # EV to Households where number
        of EVs < 2 and free parking space> 0
    else
        Clustered for Households H where number of EVs < 2 and free
        parking space> 0 do
            if H already have EV, fitness(H)++);
            for all N in N(H) do
                if N has EV then
                    fitness(H)++
                end
            end
            Assign using fitness proportionate selection #EV to
            Households where number of EVs < 2 and free parking
            space> 0
        end
    end
end
```

Algorithm 1: Simulation run

3.4. Creation and initialisation of household agent

In the model, we initialise all agent households (see Figure 3) of our substation (see the map on Fig.1) with historical load consumption data sampled for previously chosen 5 days (August 9, 2013; August 14, 2013; December 25, 2013; January 7, 2014; January 18, 2014) that represent a mix of summer and winter weekend and weekdays and one Bank Holiday. We use the same sample for all simulations, assigning randomly households to load profiles. We select EV charging patterns from a sample of charging patterns for each day of the week during one month in summer, one month in winter and bank holidays. Other parameters needed for the initialisation are EV charging patterns, initial number of households, initial number of electric vehicles, distribution type (clustered or random), and whether high, medium or low EV uptake (the uptake curves are given as csv files stating the number of EVs to be distributed in a neighbourhood in a year).

3.5. Running the simulation and output

At every time-step (1 year), a given number of EVs (decided by the given scenario) is distributed between household agents such that parameters and constraints of the model are satisfied; some of the properties of household agents are updated; and the change of load demand for every agent is recorded (refer to Algorithm 1 in subsection 3.3 for more detailed description). The output is the updated half-hourly daily profile for each household for each year. If a household acquired an EV, the corresponding EV charging pattern will be added on a top of its base-load on each of 5 selected days. The output therefore contains updated half hourly loads for all households on the five selected days.

4. Results of Experiments

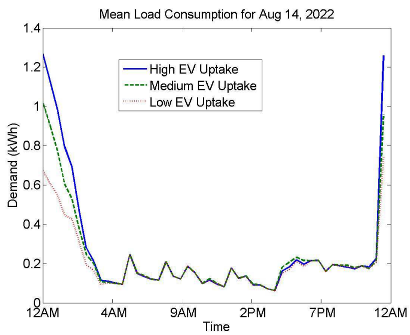
We performed multiple experiments (50, 150 and 1000 runs per experiment) for medium, high and low EV uptake scenarios for both clustered and random distributions. The results contain recorded electric load demand data for all households at half hourly resolution for the 5 chosen days in a year. The number in each period is kWh in the hour. First half hour corresponds to 12.00am-12.30am time interval.

To compare between clustered and random distributions, we pick one street on the map of the substation (see the map on Figure 1) and generate plots analysing the aggregate data for these households obtained from the forecast.

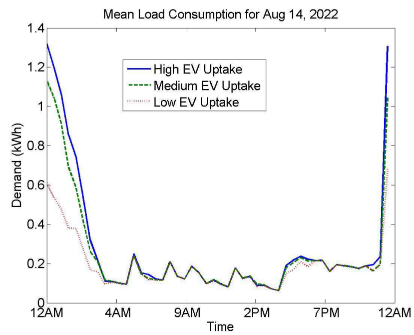
4.1. Random vs Clustered Distribution

The distribution of EVs between agents in our long term forecasting engine is implemented to be random or clustered. In random distribution any household at any time is equally likely to get an EV. In clustered distribution we distribute EVs in such a way that a household is more likely (i.e. has a higher probability) to get an EV if the household itself, or one or more of its neighbours, have an EV. The probabilities are updated at every time-step (corresponds to 1 year) of simulation. We compare all three scenarios under random and clustered distribution. The figures 8, 9 and results below compare the half hourly electricity mean and relative standard deviation (RSD) of end-user demands respectively for August 14, 2022 and December 25, 2022 correspondingly. These results are aggregated for consumers in one street only (refer to Figure 1). Small difference in peaks compared to clustered distribution can be ignored since these results are generated for one street only. Figures 8a and 9a illustrate the mean load consumption of our results for random distribution. In Figure 8a peak demands for high, medium and low EV uptake scenarios are 1.2679 kwh, 1.0221 kwh and 0.7466 kwh respectively, all occurring in the 12am-12.30am time interval. In Figure 9a peak demands for high, medium and low EV uptake scenarios are 1.3516 kwh, 1.1374 kwh and 0.8425 kwh respectively, all occurring in the 12am-12.30am time interval. As expected, the highest peaks occur for the high EV uptake, and peaks are lowest for the low EV uptake.

Similarly Figures 8b and 9b illustrate the mean load consumption of our results for clustered distribution. In Figure 8b peak demands for high, medium and low EV uptake scenarios are 1.3207 kwh, 1.1351 kwh and 0.6792 kwh respectively, all occurring in the 12am-12.30am time interval.

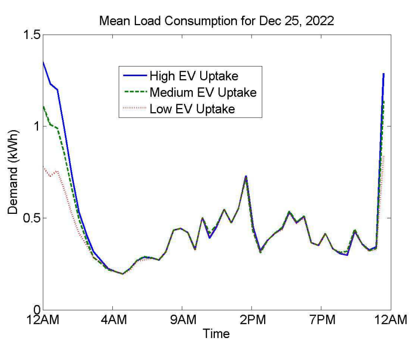


(a) EV Random Distribution

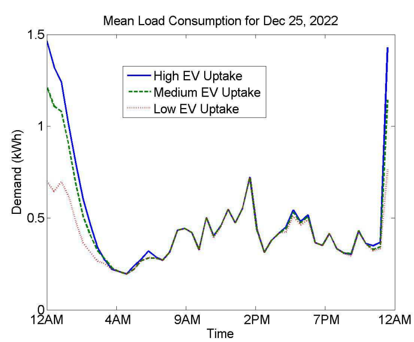


(b) EV Clustered Distribution

Figure 8: Mean load consumption for Aug 14, 2022

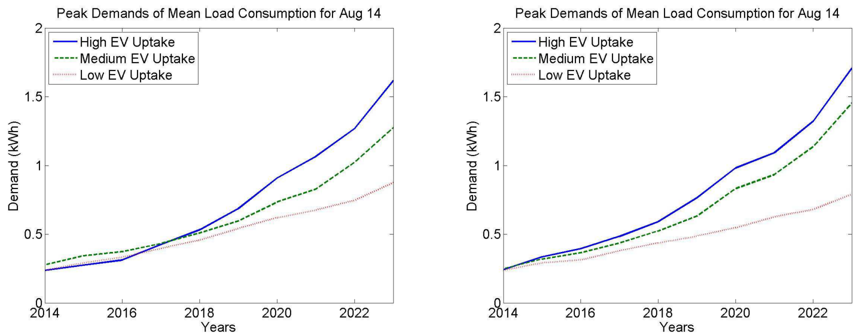


(a) EV random distribution



(b) EV clustered distribution

Figure 9: Mean load consumption for Dec 25, 2022



(a) EV random distribution

(b) EV clustered distribution

Figure 10: Peak demands for 3 scenarios on Aug 14 each year

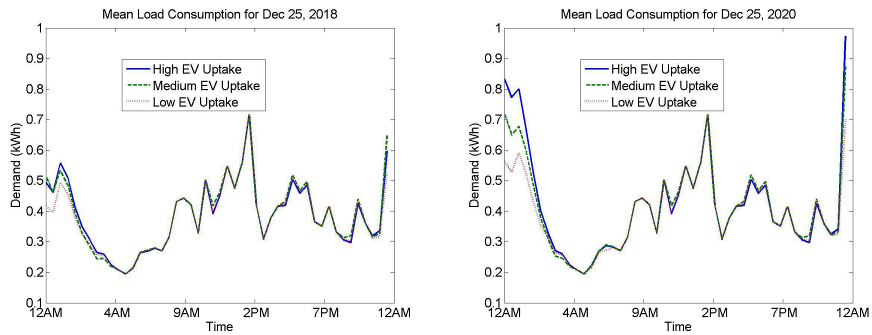
In Figure 9b peak demands for high, medium and low EV uptake scenarios are 1.4655 kwh, 1.218 kwh and 0.7637 kwh respectively, in the 12am-12.30am time interval. As expected, the highest peaks occur for the high EV uptake, and peaks are lowest for the low EV uptake.

Figure 10 illustrates the peak demands of mean daily load profiles, using the random and clustered distribution for the three scenarios for August 14 each year. Similar peak demands for the three scenarios have been observed for December 25 each year. In Figure 10a it is easy to see that up to year 2018 the peak demands are slightly higher for medium EV uptake scenario than for high EV uptake scenario. This happens since these results are aggregated for 8 neighbouring household agents (one street only) and the difference between EV uptakes for high and medium EV uptake scenarios during the first 4 years is small. From 2018 the situation changes and and the peak demands are in the expected order, where a high EV uptake means higher peak demand. Similar peak demands for the three scenarios have been observed for December 25 each year. In Figure 10b the peak demands of medium EV uptake scenario are in between peak demands for high and low EV uptake scenarios.

Another observation we can make from the results of our experiments performed for different years in 2014-2024 interval is that up to 2018 all the peaks for December 25 (Christmas day) are the same both for random and clustered distributions and occur at 2pm, which leads us to the conclusion that demand for these years is driven by general behaviour and not by EV charging behaviour. The midday peaks for December 25th shift to overnight ones after 2018 and the peaks observed for clustered distribution are slightly higher than for random distribution. The Figure 11 illustrates the results discussed above for December 25, years 2018 and 2020, random distribution.

4.2. Variation in results regarding the number of runs

To check how the spread of data changes with increasing number of runs per experiment, we performed 50, 150, 500 and 1000 runs for scenarios with



(a) EV random distribution, 2018

(b) EV random distribution, 2020

Figure 11: Peak demands for 3 scenarios on Dec 25, years 2018 and 2020, Random Distribution

random and clustered distribution. The results are consistent with the results we have obtained for 50 runs. Table 2 displays highest RSD values for random distribution on Dec 25, 2022.

DECC Scenario	**50 runs**	**150 runs**	**500 runs**	**1000 runs**
Medium EV Uptake	1.4759	1.4574	1.4561	1.4561
High EV Uptake	1.4561	1.4561	1.4561	1.4561
Low EV Uptake	1.4762	1.4561	1.4561	1.4561

Table 2: The highest RSD values for 3 scenarios on Dec 25, 2022 (random distribution).

Finally we investigated margins of error (the radii of confidence intervals) at a 95% of level of confidence for 50, 150, 500 and 1000 runs for scenarios in random distribution mode. Table 3 shows the margins of error for random distribution on Dec 25, 2022. We observe that the margins of error are getting smaller, as expected, which shows that on average we get more precise estimates from our sample for both the mean and standard deviation. Similar observations are made for the clustered distribution. However, since we observe that variability of data (relative standard deviation) does not decrease significantly with increased number of runs per experiment, it can be concluded that 150 is a sufficient number of runs per experiments.

DECC Scenario	**50 runs**	**150 runs**	**500 runs**	**1000 runs**
Medium EV Uptake	0.1576	0.091	0.0499	0.0353
High EV Uptake	0.1576	0.091	0.0499	0.0352
Low EV Uptake	0.1576	0.091	0.0499	0.0353

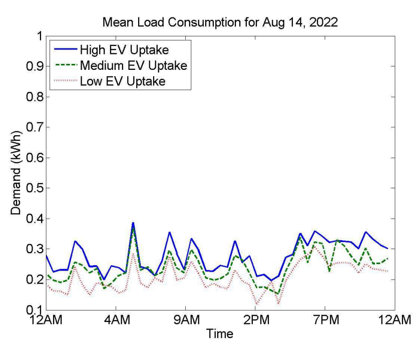
Table 3: Margins of error for 3 scenarios on Dec 25, 2022 (random distribution).

5. Experiments with altering charging behaviour

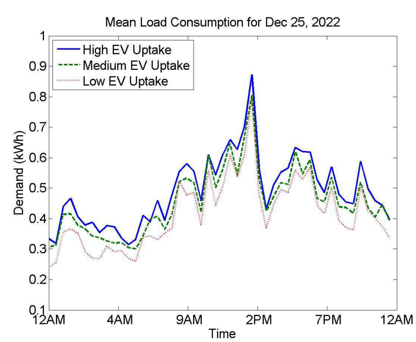
The results presented in previous section were obtained by using daily charging patterns obtained from an EV trial and according to the trial's data the customers were encouraged to charge overnight. However it is interesting to see how the change of daily EV charging behaviour affects peak loads and peak times on the low voltage network. Thus we have run additional experiments (150 runs per experiment) for 8 previously selected neighbouring household agents (one street only) altering the daily EV charging behaviour only, and comparing the results with the results from the trial data.

5.1. EV charging behaviour: random charging pattern

In these experiments we assumed that daily EV charging behaviour is random and cannot be predicted at any time. We have implemented this behaviour by randomly distributing EV charging patterns obtained from the trial's data in 48 half hour interval (see subsection 3.1). That implies that in our long term forecasting engine each household agent owning an EV adopts a random charging pattern. To make a comparison with our original results we analyse the data in the context of half hour electricity and the mean load consumption for the random distribution and the same days (August 14, 2022 and December 25, 2022) we used in section 4. Figure 12 illustrates the mean load consumption, using the random distribution for the three scenarios for August 14 and December 25 2022. For August 14 (see Figure 12a) peak demands for high, medium and low EV uptake are 0.3879 kwh, 0.3698 kwh and 0.3067 kwh respectively, high and medium EV uptake peaks occurring in the 13th half hour (06.00am) and low EV uptake peak occurring in the 38th half hour (06.30pm). In this case we observe that peak loads are significantly smaller than when EVs were charged at night time (see section 4). In our experiments with random charging patterns we get morning and early evening hour peak loads instead of previously discussed overnight ones.



(a) Mean load consumption for Aug 14



(b) Mean load consumption for Dec 25

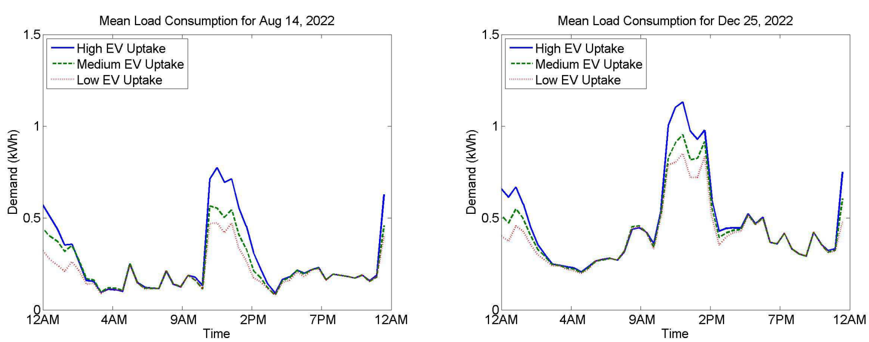
Figure 12: EV random charging pattern: mean load consumption

In Figure 12b peak demands for high, medium and low EV uptake are 0.8729 kwh, 0.8046 kwh and 0.7932 kwh respectively, all occurring in the 29th half hour (2.00pm). Here we see that unlike the case with overnight charging behaviour we observe afternoon peak loads for high and medium EV uptake. Also peak loads observed for random charging behaviour case are slightly smaller compared to peaks loads for midnight charging behaviour. This observation may be due to the fact that demand is driven by general behaviour and is not driven by EV charging.

Similar observations with slightly higher peaks and plots have been generated for the clustered distribution mode.

5.2. EV charging behaviour: equal distribution of nighttime and daytime charging patterns

In our experiments we assume that on a selected street half of the household agents owning EV(s) charge overnight and the other half charge daytime. This was implemented by shifting EV charging patterns from the trial's data (where most of EV charging happens at midnight) by 24 positions in 48 half hours interval and equally distributing EV charging patterns in the original and shifted data between household agents. To make a comparison with our original results we analyse the data in the context of half hour electricity and mean of end user demands for the random distribution and the same days (August 14, 2022 and December 25, 2022) we used in previous experiments.



(a) Mean load consumption for Aug 14

(b) Mean load consumption for Dec 25

Figure 13: EV nighttime and daytime equal distribution charging pattern: mean load consumption

Figure 13 illustrates the mean load consumption, using the equal distribution of midnight and daytime charging patterns for the three scenarios for August 14 and December 25 2022. For August 14 (see Figure 13a) peak demands for high, medium and low EV uptake are 0.7737 kwh, 0.5648 kwh and 0.4733 kwh. Here we see that unlike the case with overnight charging behaviour the peak loads for high and medium EV uptake are all achieved in 11.30am-12.00pm time interval. In this distribution of EVs we observe that peak loads are higher than the ones presented for random charging behaviour (see subsection 5.1) but lower than peak loads achieved with midnight charging behaviour (see section 4). In our experiments with equal distribution of nighttime and daytime charging patterns peak loads happen midday instead of the previously discussed morning and overnight ones.

The results obtained for Christmas day are illustrated in Figure 13b and show that peak demands for high, medium and low EV uptake are 1.1321 kwh, 0.955 kwh and 0.852 kwh respectively, all occurring in the 26th half hour (12.30pm). However peak loads observed for equal distribution of nighttime and daytime charging patterns case are slightly lower than the peaks for the overnight charging behaviour but higher than the ones achieved for random charging behaviour.

Similar observations with slightly higher peaks and plots have been generated for the clustered distribution mode.

6. Conclusions

We used an agent-based simulation to forecast individual electrical load in low-voltage network. Our model was implemented using Repast agent-based simulation libraries. Using different scenarios for EV uptake as predicted by UK department of climate change, and the real data obtained from distribution network organisation of SSEPD, we aimed to assess the future EVs impact on peak load on local networks. Simulations were run for different scenarios and an average was reported. We also looked at variations regarding the number of runs.

Our experiments with altering household behaviour show that for ordinary days peak loads and peak times are very much dependent on EV charging patterns. The results we obtained show that peak loads observed for equal distribution of nighttime and daytime charging patterns case are lower than the peaks for the overnight charging behaviour but slightly higher than the ones achieved for random charging behaviour. Thus having a variety of behaviours will reduce the peaks as expected. However on special days such as Christmas days our results for randomising EV charging patterns show that peak loads and corresponding times are mainly influenced by the base load consumption (electricity usage before EV charging).

We are aware of limits of our assumptions and data used for simulations: charging patterns are obtained from the small pilot-study, our model of social influence is relatively simple and ignores some intrinsic household characteristics such as socio-demographic profile, working and commuting patterns and so on. However, we think that there are also some obvious benefits of our model: it is relatively easy to include new features into this model given that the appropriate data is collected, e.g. sociodemographics, ownership of other low carbon technologies, geographic information systems data (GIS) etc. It is also easy to replace current governmental scenarios with updated ones as they change in future. Also our approach is scalable, as shown by running efficiently simulations on up to 30000 agents in 600 substations. Thus we believe simulations like ours can be a useful exercise for DNOs and policy makers.

From our results we conclude that overnight peaks will occur (however this is based on pilot study, where the customers were incentivised in the trial to charge overnight). Our main results show that the peak demands for the clustered distributions in comparison with the results for random distributions are higher for high and medium uptakes. This is due to people influencing each other in clustered distribution mode, and it is related to the ratio of uptake versus the influence factor. Also our results show that for random distribution up to year 2018 the peak demands on local (street or feeder) levels are higher for medium EV uptake scenario than for the high uptake one. From 2018 the situation changes and the peak demands are higher for the high than for medium one. Thus, the impact on the local network could be felt faster than predicted nationally by DECC scenarios. Also up to year 2018 for December 25th we observe similar peaks and midday peak times for both random and clustered distributions, which leads us to the conclusion that demand for these years is driven by general behaviour and not by EV charging behaviour.

6.1. Future Work

While we randomly sampled from collected EV charging data, it would be of interest to explore how the peak patterns change with random charging schedules. A promising direction for the future work would be to collect other relevant data, such as socio-demographic or attitudinal information from postcodes to form more rules. While refining agents' adoption of low carbon technologies rules, this would create more realistic environment. Last but not least, depending on available data, we plan to add photovoltaic and heat pumps to the model. While independent integration is straight-forward, it would be intriguing to see how the different low-carbon technologies interplay with each other concerning the total individual load.

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