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Validation and application of agent-based electric vehicle charging model

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Abstract

Agent-based models are a class of simulation in which many autonomous agents interact such that the mix of stochastic and deterministic actions each agent undertakes results in some emergent behaviour across the entire population. Such models have been used to explore the impacts of electric vehicles (EVs) on electricity grids. However, there has been little data available against which to validate this approach. In this study, we evaluate an agent based EV model against real data observed during the "My Electric Avenue" project; an Ofgem funded 3 year trial aiming to identify the impacts of EVs on local grids. We find that, within the constraints of the available trial data, the agent model is able to replicate dominant charging pattern features. The behaviour of owners will inevitably play a role in the actual charging patterns observed and we further explore how consumer adoption of time-of-use tariffs and vehicle range (battery capacity) preference would impact on demands at the local substation. We show that simplistic adoption of time-of-use tariffs would have undesirable consequences for network peak demands and that the expected increase in EV range and thus battery size, will both increase peaks and total energy supply to domestic properties.

Peer-review under responsibility of the scientific committee of the 4th Annual CDT Conference in Energy Storage and Its Applications, Professor Andrew Cruden, 2019.

Keywords: Electric vehicles; Agent-based modelling; Charging profiles; Distribution network demands

1. Introduction

Electric Vehicles (EVs) are expected to provide a significant contribution in the drive to reduce carbon emissions and local air pollution from personal transport [1]. Bloomberg [2] estimates that global sales will increase from 1.1 million in 2017 to 11 million by 2025 and 30 million by 2030, with around 1/3 of the global car fleet being electric by 2040. The UK's National Grid Company [3] forecasts a similar level of penetration under its Future Energy Scenarios 'Consumer Power' projection. These levels of penetration may pose issues for electricity networks due to high localised charging demands and the potential to breach cable thermal limits and statutory voltage constraints. Ihekwaba et al. [4] use a detailed local network model combined with a charge profile developed from the American

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National Household Travel Survey to analyse the impact of EV charging on voltage compliance and conclude that non-compliance at the remote end of feeders may occur at as little as 20% penetration. Papadopoulos et al. [5] use both a deterministic and stochastic approach to model a generic UK urban network with vehicles arriving at homes between 5 pm and 6 pm, coinciding with the normal peak demand. They conclude that voltage and thermal constraints would be breached in the case of medium (33%) household penetration of EVs and that the distribution transformer would be overloaded even at low (12.5% of households) penetration. For a specific test network based on a suburban Dublin residential feeder, Richardson et al. [6] identified a 20%–40% EV penetration threshold beyond which safe operation limits would be exceeded. The uncertainty in this range is due to varying topology and phase imbalances in the network studied.

Several trials have also been run [7–9] to establish real-world impacts. The "My Electric Avenue" (MEA) project [7] was initiated in November 2012. A partnership between UK universities, industry and network operators, it comprised real-life trials in localised clusters and a broader social group in order to better understand EV use and charging characteristics. In total 200 EVs were included in the trial from January 2014 to June 2015. The trial also included the use of a sub-station level load management scheme that could reduce feeder load by controlling EV charging using powerline communications and house and workplace charger switching circuits. The project results indicated that some 32% of low voltage feeders across Britain would require intervention when 40%–70% of customers have EVs; this real-world evaluation is thus somewhat in conflict with theoretical studies. The broad range here occurs for similar reasons as with the study, but with a higher penetration level due to more diverse consumer charging strategies.

Richardson [10] notes the need to improve the fidelity in regard to vehicle use and charging profiles to better understand the impacts of EV adoption on networks and renewable integration. Agent-based models are a class of simulation in which many autonomous agents interact such that the mix of stochastic and deterministic actions each agent undertakes results in some emergent behaviour across the entire population. Such models offer the prospect of improving the accuracy of EV adoption and use modelling. In this paper we apply an agent-based EV model and seek to show that this approach can replicate real-life EV use and its impact on network demands. The use of agent-based modelling enables more sophisticated approaches to the timing of charging demand and the types of vehicles connected. In this paper, we add to the existing knowledge in this area by considering the impact of increasing EV battery size on domestic charging profiles.

Section 2 briefly describes the agent-based model and Section 3 develops a case study in which the outputs from the model are compared to data from the MEA project. In Section 4 the MEA data is replaced with more generic data from the UK National Travel Survey (NTS) [11] and the impact of two charging regimes and battery sizes on the diversified load profile are considered. Section 5 summarises the findings and details further work to be undertaken.

2. Agent model overview

The agent-based model comprises households, car-owners and car agents. In this application, cars were modelled on the 24 kWh Nissan Leaf with 3.6 kW charging used in the MEA trials. Given that battery sizes are increasing to meet consumer demand for longer range vehicles, we also model a vehicle identical to the leaf but with a 64 kWh battery, representative of the current generation appearing in the market. The energy efficiency of these larger battery vehicles is assumed to be the same on the basis that the latest generation of vehicles exhibit improved energy efficiency despite the greater weight of batteries. (For comparison, a 64 kWh Hyundai Kona has a an estimated real-world efficiency of 260 Wh/mile, 6.15 km/kWh, compared to the 2013 24 kWh Nissan leaf at 250 Wh/mile, 6.43 km/kWh [12].) Car-owners undertake journeys defined within a database populated either from the MEA case study, or using samples from the NTS mixed with additional random journeys based on NTS timing and distance distributions. The NTS dataset includes only one week of detailed data from each car-owner and thus becomes a deterministic dataset when repeated over time. Adding random journeys is both required to match the average distance travelled to the UK average and to inject randomness into the model after the first week. Fig. 1 illustrates the basic agent drive-cycle process. The NTS or MEA journey data was contained in a database and read into a function in the simulation which triggered a driving event at the required start time for each agent journey.

Fig. 2 presents journey speed vs. distance from NTS summary data, which provides speed data across a range of trip distance bands. For each journey undertaken, a vehicle speed was determined using a PERT distribution parameterised from the data in Fig. 2. From this assigned speed an estimate of the efficiency of the vehicle (km/kWh)

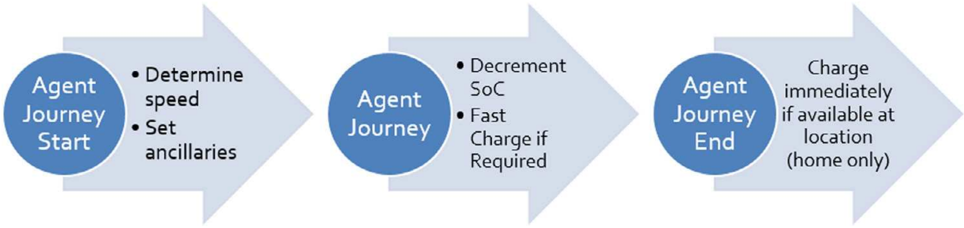

Fig. 1. Flow diagram of agent drive-cycle process showing mean vehicle speed and ancillary power assignment, continuous decrement of SoC during journey and destination charging process.

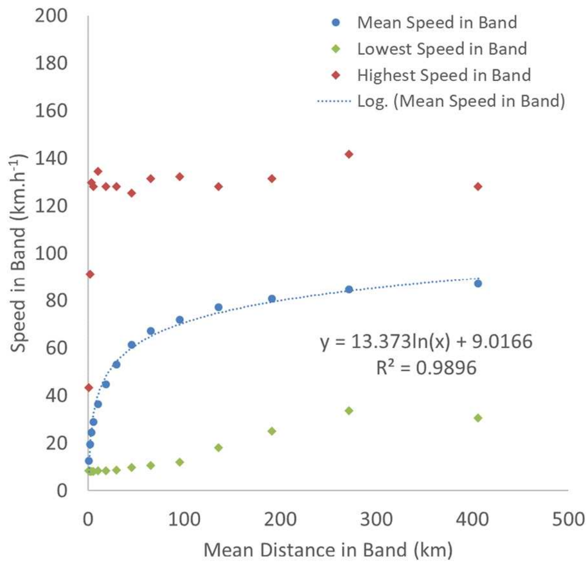

Fig. 2. Minimum, maximum and mean speed plotted against the mean distance of a journey from NTS data; used to determine speed from which vehicle energy economy is estimated.

for each journey was determined using the data presented in Fig. 3. The data was sourced from EV Enthusiast [13,14] and Manufacturer [15] web sites and are of the form that would be expected from theoretical analysis and practical trials as illustrated by Lee and Choi [16]. Given the close match between the Tesla roadster data (available over a more comprehensive speed range) and that of the Nissan Leaf over the smaller range for which data is available, the Tesla curve was used to determine energy economy in the model.

Eq. (1) summarises how each EV battery was discharged and charged in the simulation. During each journey, the state of charge (SoC) of the battery was decremented at a rate based on the energy economy of the EV assuming that the journey was undertaken at constant average speed determined from the journey length as previously described. An additional uniformly distributed random ancillary equipment load between 0.5 kW and 1.5 kW was added to this rate. If the SoC of the battery reached 5%, then an immediate rapid charge was initiated; there was no attempt in this model to simulate the process of locating and driving to a rapid charger during a journey. Rapid charges were assumed to take the battery from 5% SoC to 80% SoC at an average charge rate of 50 kW.

$$S\dot{o}C = \begin{cases} -\left(\dfrac{v_{n,j}}{\eta_{n,j}} + A_{n,j}\right) & \textit{during scheduled journey} \\ 0 & \textit{When parked at non} - \textit{charge location} \\ \eta_c P_h & \textit{on arrival at home}, SoC < 100\% \\ \eta_c P_r & \textit{during scheduled journey on } SOC \leq 5\% \textit{ until } SoC \geq 80\% \end{cases} \tag{1}$$

where

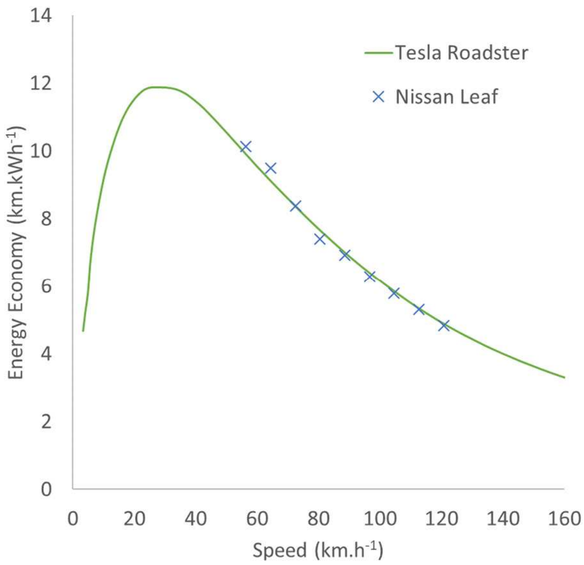

Fig. 3. Nissan Leaf [17] and Tesla [15] energy economy plotted against speed.

v_j (km h^{-1}) a PERT distribution where parameters are determined from Fig. 2 and journey distance is from NTS

η_j (km kWh^{-1}) function defined by the parameterised Tesla curve in Fig. 3

A_j (kW) ancillary load, uniformly distributed between 0.5 and 1.5 kW

$\eta_c = 0.875$ (N/A) Charging efficiency (assumed constant regardless of charge rate)

$P_h = 3.6$ (kW) home charge rate

$P_r = 50$ (kW) rapid charge rate (during journeys)

The NTS data includes information on the destination for each journey and this was used to determine whether the vehicle was charged at that destination. For the purposes of this analysis owners were assumed to have access to home charging and to always plug-in on arrival at home, but did not charge at any other destination. Charging was assumed to operate at a continuous 3.6 kW (the same as the rating in the MEA trial) until the battery was fully charged. This is a simplification since actual charge rates are reduced as the battery approaches 100% SoC. Data on EV charging efficiency is limited, Kieldsen et al. [18] indicated charging efficiencies of 70%–90% for a Nissan Leaf depending on test method. However, all methods consider only the final 20% of charging; given that charge rates reduce as the battery reaches 100% SoC, and the authors indicate converter efficiency is sub-optimal when operating below design point, we have adopted a charge efficiency of 87.5%, close to the maximum indicated.

The simulation continuously updated total power demand across all charging activity and also determined a household demand, taking account of those households with more than one EV. The total demand was also converted to a household half-hourly average demand profile for comparison with non-EV household electricity consumption. Charging from rapid chargers was also accumulated, although in the case of the MEA data, there were no rapid charging requirements.

3. Model validation against MEA data

The MEA dataset provides trip data from the Nissan EV portal including start date/time, end date/time, trip distance and power consumed. In addition, each car-owner's home was fitted with charge-point voltage and current logging and information on the state of the charge-controller switch, which could remotely control charging of the vehicle. Since the agent-based simulation does not model household (or substation) power flows, only those weeks and owner groups for which there were no remote switching operations were chosen for the analysis. This resulted in 5 separate weeks and up to 27 households in each week. A shortcoming of the MEA data is that there is no information about trip destinations and therefore the location of vehicles when charging is unknown. To develop travel profiles for each individual that were compatible with the NTS data used in the agent-based model it was necessary to make assumptions about driver destinations. Table 1 lists the assumptions used to convert the MEA data to NTS (agent model) compatible data.

Table 1. Assumptions used in developing travel profiles.

Trip start time range	Assumed origin	Assumed destination	Charge on arrival
0600–0900	Home	Work	No
0900–1700	Work	Work	No
1700–1900	Work	Home	Yes
1900–0600 (+1 day)	Home	Home	Yes

Fig. 4 shows the correlation between the MEA data and agent-based model over one week of charging data for a group of 27 households. This chart shows reasonable time-correlation between the charging events but poor correlation in regard to total energy. However, further analysis of the data indicates this to be the result of the simplified assumption set described previously and frequent charging of vehicles by car-owners when not at home.

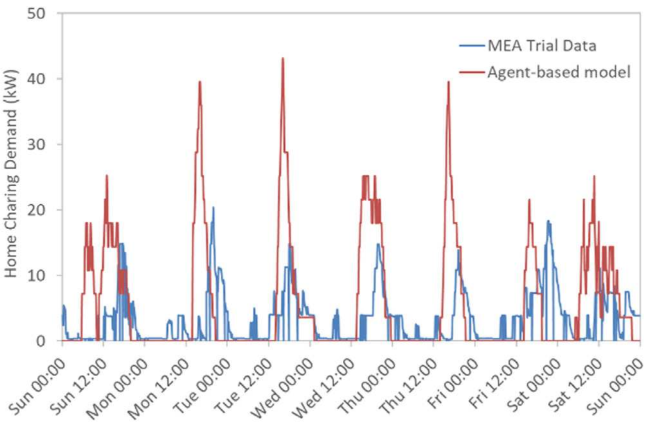

Fig. 4. Comparison of MEA and agent-based simulation total home charging demand over one week for 27 car-owners showing additional day-time charging and lower overall energy use in real world data resulting from un-specified charging events and data conversion approach.

This can be verified from the Nissan EV data, which shows 1168 kWh of energy consumed by vehicles during trips, where the MEA home charging data shows only 580 kWh charged. In comparison, the agent-based model delivers some 1500 kWh of energy to the vehicles over the week. The model uses a charge efficiency of 87.5%, so energy consumed in the model is 1313 kWh, a +12.4% error. Given the uncertainty in the charge efficiency and that the battery State of Charge (SoC) at the start and end of the trial week is not accurately known, this can be considered a reasonable result. Some of this error may also be attributable to using a conservatively high range (0.5–1.5 kW) for vehicle ancillary power consumption.

The simplified assumptions in regard to vehicle location, and therefore ability to charge, would also tend to result in the high peaks seen in the data, since any trip ending after 1700 will result in the car being charged immediately with more overlapping of charging due to longer average charge times per vehicle. The smaller peaks in the MEA data during the day reflect daytime journeys when the car is plugged in on return to home and which are also not picked up by the assumptions in Table 1. The 24 kWh profile in Fig. 5, for a random collection of NTS journeys, includes rapid charging demands, which can be observed as the short peaks of 50 kW and above. When these are excluded, it can be seen that the profile has a more similar shape to the MEA data (which itself tends to be step-wise due to the small sample size) and with smoother power variations and generally later peaks. Thus we see that the agent based approach has the capability of producing reasonably accurate charging profiles based on journey data

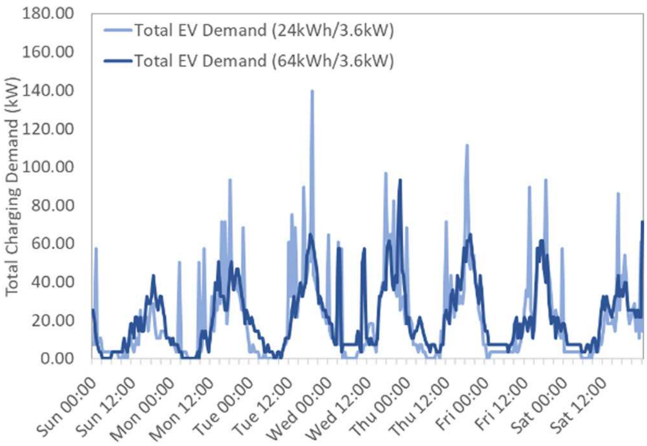

Fig. 5. Total charging demand for fleet of 100 24 kWh or 64 kWh EVs based on 'Uncontrolled Charging' scenario, and showing non-domestic fast charging.

available in the NTS. Such models are also ideally suited to adding more detailed behavioural response through which better matching of real-world charging patterns may be obtained.

4. Impact of charging strategies

In this section, the impact of different charging strategies on diversified household demand is investigated. We use a sample of 100 car owners from the NTS to represent the demand that might be placed on a typical residential feeder. The Energy Networks Association [19] reports that low voltage feeders may have from 1 to 500 connected customers; other studies [5] indicate 15 to 150 customers per feeder, each of which may have more than one vehicle, thus a feeder of 100 car owners appears consistent with other studies for analysis where there is high penetration of EVs. Fewer customers would result in lower demand diversity, whilst more customers would imply greater diversity and a likely smoothing of the impacts illustrated here.

Existing diversified household demand is assumed to match Profile Class 1, domestic unrestricted customers [20], though we also consider class 2 for domestic economy 7 (time of use tariff or ToU) customers. These profiles are used by Elexon, who are responsible in the UK for financial settlement of the electricity market, and are intended to be representative of the average (diversified) demand of a large population of the specified class of consumer. Profile Class 1 is the most common consumer type who use gas for heating whilst class 2 are consumers who use overnight electric storage heaters. The charts presented here use the winter class profile (as the worst-case peak) and show the effect of adding diversified (mean household) EV charging demand under various scenarios to that base household demand. Fig. 5 illustrates the total charging demand inclusive of rapid charges that occur outside of the domestic environment and would therefore not be part of diversified domestic demand. This chart is insightful in that it clearly illustrates that increasing battery size reduces the frequency of rapid charging and consequently increases energy transferred during home charging. In the uncontrolled 3.6 kW charging scenario, the additional energy charged at home with a 64 kWh battery compared to a 24 kWh battery is circa 22% averaged across all households. This effect occurs because EV owners with 64 kWh batteries can make nearly all of their journeys without charging away from home and thus consume more power recharging from longer journeys on their return.

Fig. 6 shows how the diversified demand profile with 3.6 kW charging would change with all consumers adopting an uncontrolled 'charge as soon as home' strategy. This results in a peak charging demand overlaid onto the normal domestic peak, leading to a 63% increase in domestic diversified peak demand. Fig. 7 shows how this profile would change with 64 kWh batteries in all vehicles, with greater energy being charged at home and a marginally higher peak demand caused by more overlapping of car charging.

In Fig. 8 we assume that the market continues to offer a simplistic Time of Use (ToU) tariff and that all consumers adopt this solely to reduce the cost of charging their vehicle and use either an on-board vehicle timer or charge timer set to the start time of the tariff. As a result of this strategy, the additional charging demand is effectively

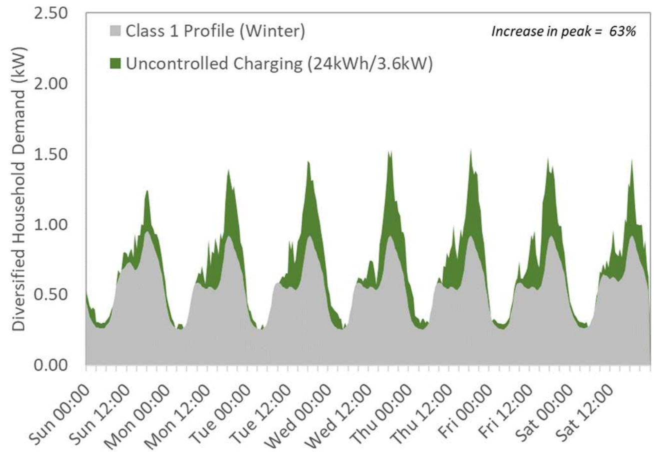

Fig. 6. Diversified domestic demand based on uncontrolled charging scenario with 3.6 kW charging and 24 kWh battery, illustrating 63% increase in peak diversified demand.

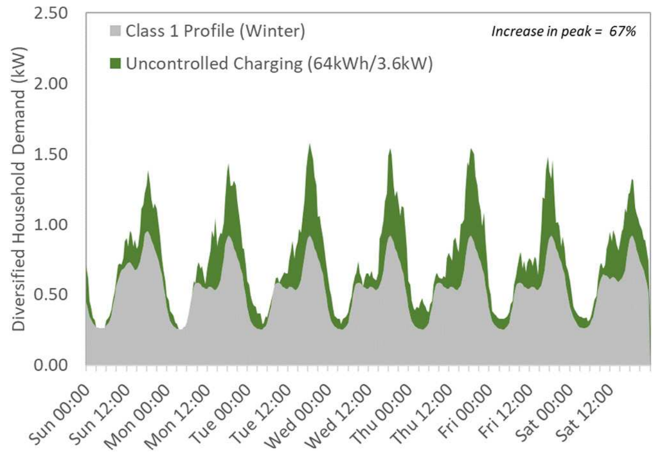

Fig. 7. Diversified domestic demand based on uncontrolled charging scenario with 3.6 kW charging and 64 kWh battery, illustrating 67% increase in peak diversified demand.

overlaid onto a standard Class 1 profile since we can assume the consumer will not have converted heating to electric heating, which is the key factor behind the difference in a Class 1 and Class 2 profile. Where consumers are already using electric heating, the impact is shown in Fig. 9; both these scenarios indicate a circa 150% increase in peak demand.

In Fig. 10 we consider the impact of increasing charging rates to 7.2 kW, a common current standard. With 24 kWh battery cars, there is now an 82% increase in peak compared to 63% with 3.6 kW charging; i.e. not in proportion to the increase in charging since there is now less overlap of charging periods. However, with 64 kWh battery cars where more energy is charged at home due to reduced fast-charging, the peak increase is substantial at 142% (Fig. 11) as those cars that have travelled long distances during the day overlap with other cars returning to charge. Increasing the charge rate to 7.2 kW where simple ToU tariffs are employed results in a potential increase in peak of 266% (not charted here).

5. Conclusions and further work

This study has demonstrated that agent-based simulation of EV use and charging demands can render a good approximation to real-world power system demands. Some additional scenarios considering a proportion of daytime

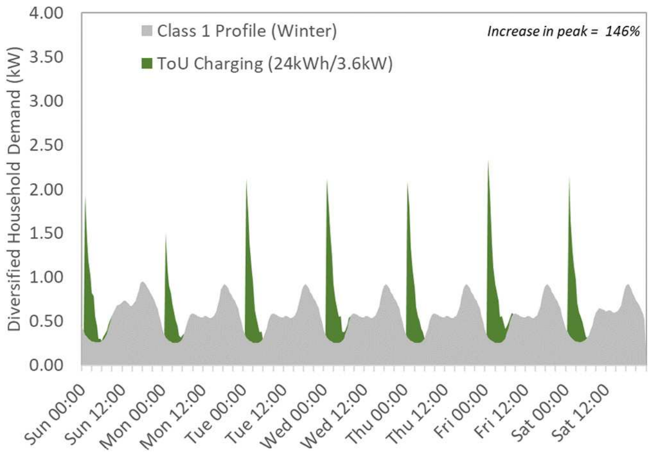

Fig. 8. Diversified domestic demand where all consumers adopt simple ToU tariff charging where car is set to start charging at start of tariff. Here consumers are assumed to use the tariff solely for car charging and therefore the diversified demand is overlaid onto a Class 1 Profile.

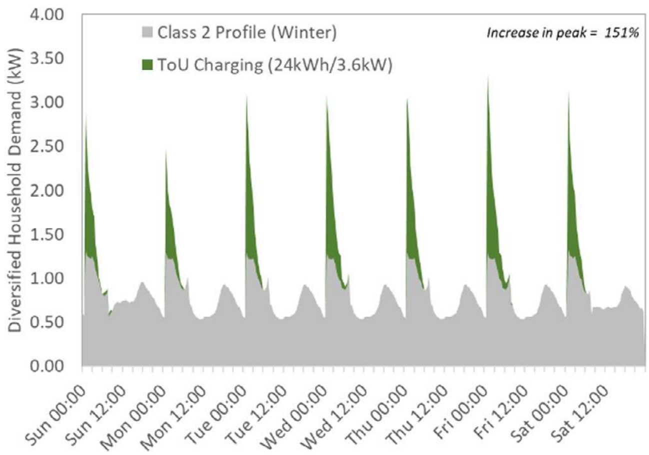

Fig. 9. Diversified domestic demand where all consumers adopt simple ToU tariff charging where car is set to start charging at start of tariff. Here consumers are assumed to be generic Economy 7 customers and therefore the diversified demand is overlaid onto a Class 2 Profile.

journeys ending at charging destinations could elicit a closer match to the MEA data, but there is no firm information on which to base such assumptions. The data-collection approach for any future real-world studies might thus be enhanced to improve the accuracy of such models. This might include, for example, a conversion of car location at each stop/charge event from its GPS to a location type (home, work, shopping etc.); this strategy would ensure data privacy whilst providing valuable information on distances travelled and charging patterns.

Earlier studies have demonstrated the impact of EV charging on distribution system demands and the need for system reinforcement and/or controlled charging systems. In this study we have added greater fidelity to the travel patterns of car-owners and confirm the findings of those earlier studies, with peak demand increases of around 60% demonstrated where no charge control is implemented. This work has further identified that EV battery size can have a significant impact on domestic peak demand as well as on total household energy supplied. Consumers are expected to adopt cars with larger batteries than are historically the norm in the EV fleet so this finding is significant.

One advantage of using agent-based modelling here is in the application of behavioural modelling; we intend to publish further studies investigating how more realistic consumer behaviour is likely to impact on domestic demand profiles and the application of autonomous car charging control to reduce distribution network peaks.

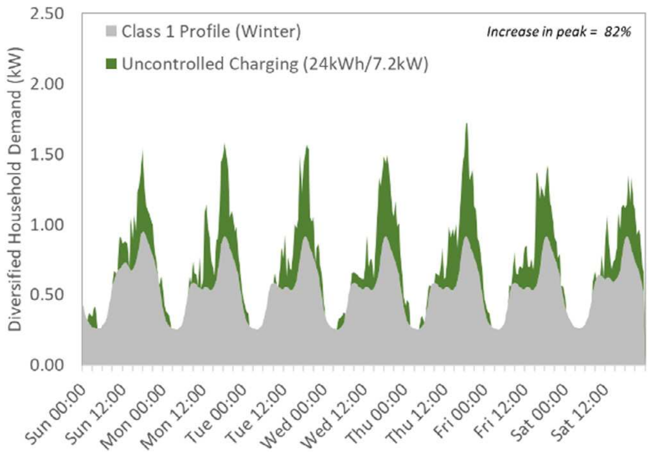

Fig. 10. Diversified domestic demand with uncontrolled charging and 7.2 kW chargers, 24 kWh batteries, illustrating 82% increase in peak demand.

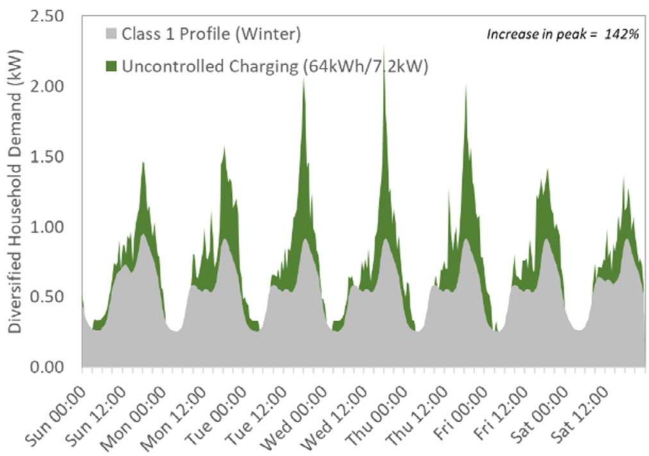

Fig. 11. Diversified domestic demand with uncontrolled charging and 7.2 kW chargers, 64 kWh batteries, leading to a 142% increase in peak demand.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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