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Long term individual load forecast under different electrical vehicles uptake scenarios ☆

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HIGHLIGHTS

- We create agent-based model to forecast individual electrical load in LV network.
- Using different scenarios we assess the future EVs impact on peak load.
- Ordinary days peak loads and peak times are dependent on EV charging patterns.
- Having a variety of EV charging patterns may help to reduce the peaks.
- The impact on the local network could be felt faster than predicted.

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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.

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 8–15 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

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is increasingly popular in this field. Agent based modelling 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 modelling 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 characterise 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 [6,7] 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.

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 [16,12]. 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 behaviour, 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, CO_2 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 [22–26]. 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,

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