STOCHASTIC ANALYSIS OF THE IMPACT OF ELECTRIC VEHICLES ON DISTRIBUTION NETWORKS

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ABSTRACT

Advances in the development of electric vehicles, along with policy incentives, will see a wider uptake of this technology in the transport sector in future years. However, large penetrations of EVs could lead to adverse effects on power system networks, especially at the residential distribution network level. These effects could include excessive voltage drop and thermal loading of network components. A stochastic method is developed to take account of the uncertainties associated with EV charging and the technique is implemented on a residential test network using power system simulation software. The results show how voltage levels, component loading network losses are impacted from EV charging, taking into account the probabilistic behaviour of the EV owners.

INTRODUCTION

Electric vehicle technology is seen by many countries as a key component in the effort to reduce harmful greenhouse gas emissions, while also reducing the dependence on imported petroleum within the transport sector. As a result, many automotive manufacturers have placed increased emphasis on the development of various types of electric vehicle (EV). These include fully-electric EVs, which operate purely from battery power, and plug-in hybrid electric vehicles, which operate on power from a combination of an on-board battery and a combustion engine. The batteries for both types of technology can be recharged from external energy sources, e.g. an electricity network.

The introduction of EV technology will not only have a significant effect on the transportation sector, but also that of electric power systems. Distribution networks are designed and rated to deliver electricity depending on the number of customers in any given area and the historical electricity demand data for each of those customers. The widespread implementation of EVs into the private vehicle fleet will lead to a significant increase in electric energy being required for the purposes of recharging the EV batteries. This would introduce new customer demand patterns at the distribution level, which could cause adverse effects to the network's operating conditions in areas where large groups of EVs are charging simultaneously. Such

effects could include excessive voltage variations, increased thermal loading and higher network losses.

Previous studies have sought to investigate the impact from large numbers of charging EVs on network infrastructure in terms of voltage deviations, increased loading, impacts on efficiency and loss of life for network assets [1, 2, 3]. Each of these studies utilised deterministic methods to assess the effect of EV charging on the distribution network by assuming, for example, fixed EV locations or fixed battery types.

This work utilises a stochastic method to assess the network impact from EV charging while incorporating a number of uncertainties inherent with EV usage. Such uncertainties can include location, EV type, energy usage and connection time. Previous studies utilising stochastic techniques have been undertaken, albeit with differing EV usage uncertainties taken into consideration [4, 5]. Taking account of such uncertainties, as well as uncertainty in the underlying residential load, should provide a more reliable insight into the potential effects of EV charging on low voltage (LV) network operating characteristics.

METHODOLOGY

A stochastic analysis technique has been developed to incorporate certain uncertainties inherent with EV charging on a LV residential network. This includes uncertainties which would be predetermined before each simulation (e.g. EV location, EV type) and uncertainties which would be determined throughout the simulation (e.g. connection times and energy requirements). The method uses predefined probability distribution functions (PDFs) to determine both the behaviour of the residential load on the network and the EV load. These PDFs are based on either real data obtained from field trials or data created to represent expected EV usage patterns. Each of the uncertainties are outlined in detail in the following section along with their respective PDFs. The program generates both residential customer demand profiles as well as EV charging profiles for a one year period. A summary of the method is given in Fig. 1.

Once the load profiles for each household and EV have been generated, an unbalanced, 3-phase, load flow, time-series analysis is implemented on a test network in order to determine the impact from EV charging using power system

analysis software [6]. The impact on voltage levels, thermal line loading and network losses can be determined from this analysis.
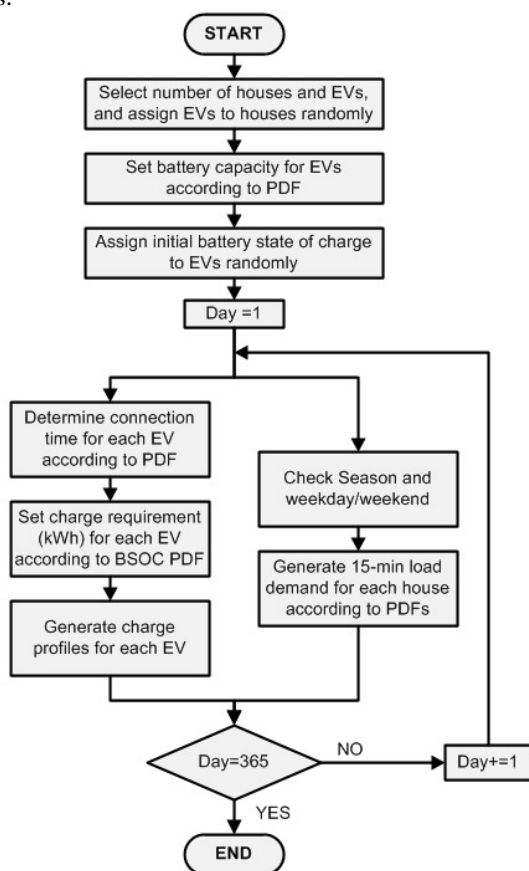

Fig. 1 - Flow chart of annual load profile generator for EVs and households

NETWORK MODEL

Test Network

The test network used in this study is representative of a LV distribution feeder in a suburban area in Dublin, Ireland. A schematic diagram of the feeder is given in Fig. 2. The radial feeder supplies 74 residential household customers and is fed via a 400 kVA transformer, which steps the voltage down from 10 kV on the medium voltage (MV) side to 400 V on the LV side. The feeder consists of 432 m of 3-phase, underground mains cable and a total of 2,160 m of single-phase service cable.

For the most part, LV substation transformers in Ireland do not have tap-changing capabilities, which is the case for the transformer modelled in the test network. As a result, the sending voltage at the substation bus is set at -3% of nominal, which takes into account the expected voltage drop on the MV network from the MV transformer to the LV transformer. It is standard practice for the distribution system operator (DSO) in Ireland to model networks in this manner for LV network analyses. The allowed voltage range

on the LV network is +/-10% of nominal (i.e. 230/400 V) [7]. Specifications for the network model components were supplied by the DSO.
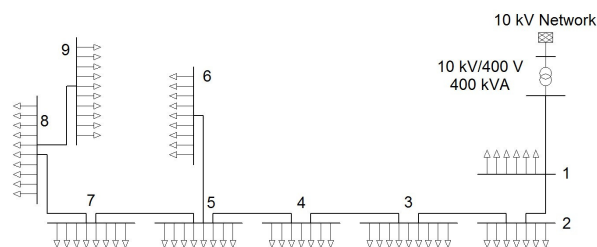

Fig. 2 - Network diagram of LV distribution feeder

Residential Load Modelling

Typical load data for domestic electricity demand customers was obtained from the DSO consisting of 15-minute time-series demand data for high, medium and low use customers over a one year period. PDFs for residential customer load were then defined for use in the stochastic program. These PDFs were then further refined to account for both seasonal and weekday/weekend variations. In Ireland, peak load for the electricity system occurs in winter time. An example PDF for a residential customer load in both winter and summer is shown in Fig. 3. Both PDFs represent the probable load at 6 pm on a weekday.
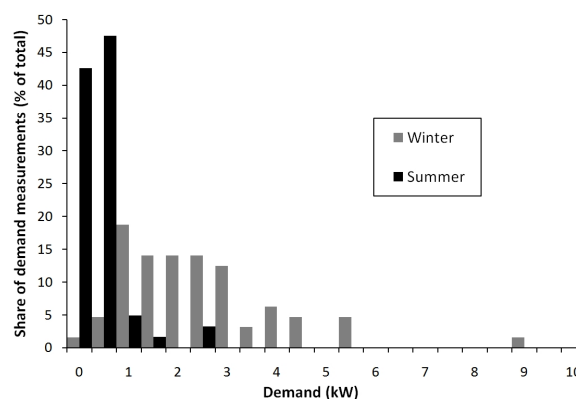

Fig. 3 - PDF of summer and winter customer demands at 6 pm on a weekday

For modelling purposes, the power factor for each household load was set at 0.95 inductive throughout the year. Each load is modelled as a combination of 50% constant power and 50% constant impedance for voltage dependency purposes.

Electric Vehicle Load Modelling

When determining EV charge profiles, it was necessary to determine certain parameters prior to the creation of the charging profiles, including which households would own an EV. Depending on the particular penetration level of EVs to be investigated, vehicles would be randomly

assigned across the network with the condition that only one EV could be assigned to a household for each simulation. It is assumed that each EV is connected at the same customer point of connection (CPOC) as the household load through a single-phase connection. 3-phase charging, fast charging and vehicle-to-grid modes are not considered here. The charge supply equipment for each EV has a charging rate of 4 kW, with an efficiency of 90%, which is appropriate in terms of the power delivery capabilities of existing LV distribution networks in Ireland. EV batteries are modelled as constant power loads with unity power factor.

The battery capacity for each EV in the model is determined a priori, based on the EV battery capacities of vehicles which are expected to be introduced to the automobile market in future years. They are based on both fully-electric (16/20 kWh) and plug-in hybrid EV (8 kWh) technologies. Each EV in the network is assigned a battery capacity based on a PDF of likely capacities. Each of the above parameters remain fixed for a one year period, but are redefined for each new year of load data.

At the start of each day, the connection time for each EV is determined using a PDF for typical connection times based on actual data collected from EV trials in Ireland. This data was collected form EV owners with no controlled charging capability and no time-of-day incentives. Fig. 4 shows the PDF for EV connection times over a 24 hour period. For this sample, the majority of connection times take place after 8 pm, which happens to avoid the typical winter residential daily load peak, which normally occurs between 5 pm and 7 pm.
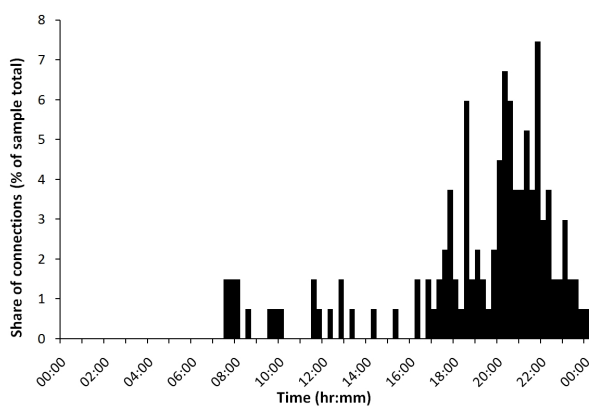

Fig. 4 - PDF of EV connection times over 24 hour period

The battery state of charge (BSOC) for each EV at the time of connection is determined in a similar manner to the connection time. However, as no actual BSOC data was available, these PDFs were created for the purposes of this study.

RESULTS

The stochastic technique is implemented for EV penetration levels of 10% and 50%. Load control capability and financial incentives are not considered in this analysis. Load-flow simulations were subsequently performed, with voltage levels measured at CPOCs, along with cable loading and network line losses. Illustrative results given below compare simulation outputs for both summer and winter scenarios.

Voltage Levels

Voltage levels at the CPOCs for households located at mini-pillars 8 and 9 (Fig. 2) were recorded. Fig. 5 and 6 show the voltage probability distribution for both the summer and winter scenarios. While there is an overall decrease in the voltages experienced in the winter scenario, the lower acceptable limit (i.e. 0.9 pu) is exceeded less than 3% of the time in both scenarios. As expected, increasing EV penetration levels result in lower voltages being observed.
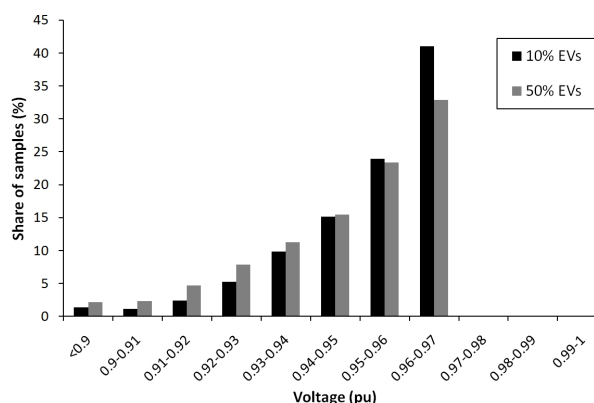
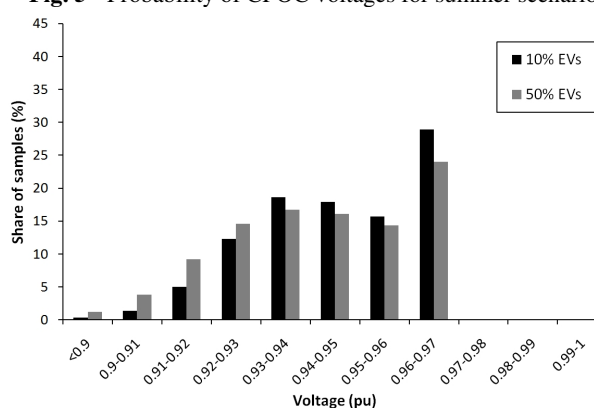

Fig. 5 - Probability of CPOC voltages for summer scenario

Fig. 6 - Probability of CPOC voltages for winter scenario

Cable Loading

The thermal loading of the mains cable supplying the feeder from the MV/LV transformer was recorded for both the summer and winter scenarios, Fig. 7 and 8. While a general increase in cable loading can be observed in the winter case when compared to the summer case, the cable exceeds its maximum rated loading less than 2% of the time. While the

probability of exceedence is similar for both winter and summer, loading levels were recorded as high as 127%.
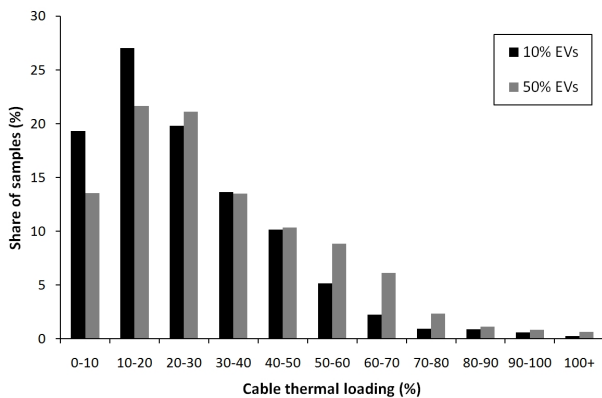

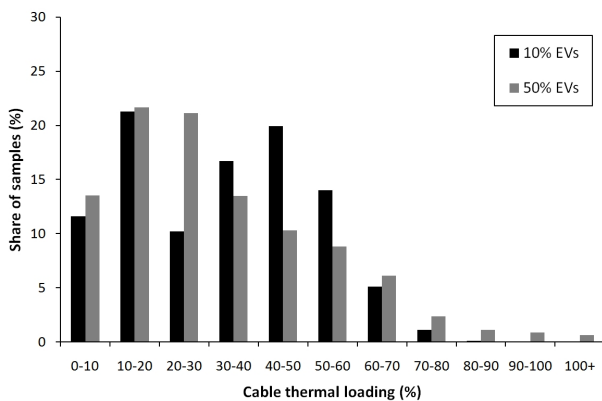**Fig. 7** - Probability of thermal loading on feeder cable for summer scenario

Fig. 8 - Probability of thermal loading on feeder cable for winter scenario

Feeder Losses

The total losses from the feeder cables are shown in Fig. 9. Results for the different EV penetrations for both seasonal cases are given.
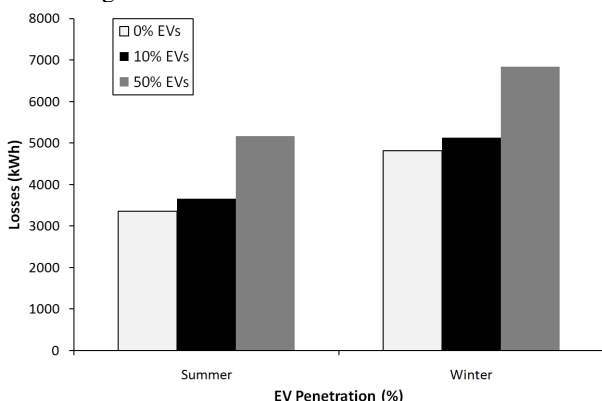

Fig. 9 - Average seasonal feeder line losses

CONCLUSIONS

This paper has demonstrated the potential impact from EVs on a LV residential distribution network using a probabilistic technique. Illustrative results have been shown

for both low and high EV penetrations taking into account various uncertainties associated with EV usage. Although these results indicate that the network limits are rarely exceeded, this may not be the case for other LV networks. If the typical connection time for EVs (Fig. 4) coincided more with the existing residential load peaks, occurrences of under-voltage and high cable loading could increase significantly. This uncertainty would also be greatly affected by the introduction of controlled charging and time-of-day pricing, and will be considered in future work. It would also be beneficial to monitor the allocation of EVs across the 3 phases of the network for each simulation. Due to the unbalanced characteristics of LV networks, an uneven allocation of EVs on one of the 3 phases may increase the voltage drop on that phase. Such analysis will also be included in future work.

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