Predicting Electric Vehicle Impacts on Residential Distribution Networks with Distributed Generation

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Abstract— **Battery charging of Electric Vehicles (EVs) will increase the power demand in distribution networks. It is anticipated that this will cause voltage drops, thermal overloads and an increase in losses. These impacts will be affected by the behaviour of the owners of EVs. A typical 3-phase LV residential distribution network model is used to evaluate the effects of EV battery charging on distribution networks with Distributed Generation (DG). The uncertainties associated with the ownership of EVs, the rating of charging equipment, the occurrence and the duration of charging, together with the spatial distribution uncertainties of DG installation, were addressed with a probabilistic approach. A case study was performed for the year 2030, considering three EV and two DG penetration levels. A control function which reschedules EV battery charging was defined based on customer preferences and distribution network constraints. Thermal overloads, voltage drops, and losses associated with each case were reported. The effects of the coordinated EV battery charging on these impacts were analysed.**

Keywords- ***Distribution Networks, Electric Vehicles, Stochastic Simulation, Distributed Generation, Smart Charging***

I. INTRODUCTION

Concerns over increased emissions from road transport are driving the transition of the transportation sector towards electrification. Electric Vehicles (EVs) will be connected to the power network via public or private chargers and consequently will rely on distribution network connections to obtain electricity for their battery charging. Large deployment of EVs may overburden the components in existing distribution networks and is anticipated to modify the voltage profile of distribution feeders [1].

A number of studies investigating the impact of dispersed EV battery charging on distribution networks have been completed. Some considered uniform EV allocation among LV feeders [2, 3] while others utilised probabilistic approaches to tackle the uncertainty of spatial EV battery charging [4, 5].

Managing EV battery charging may defer infrastructural update investments and reduce the impact of EV charging on distribution networks. Smart charging of EVs, was defined in [2], as the coordination of charging EVs in order to avoid voltage limits violations and power line overloading. In [3], smart charging control was considered to charge EV batteries in a way that enables uniform distribution transformer loading to be attained during a day. The authors of [4] used optimisation software to match predefined EV charging schedules in order to improve feeder voltage profiles and minimise power line losses.

The strategies which can be followed to manage the charging and discharging of EVs are studied in [7].

This research work considered the following uncertainties for studying the network impacts arising from EV battery charging: (i) Type of residential load, (ii) EV location, (iii) Rating of EV charger, (iv) EV charging occurrence and (v) EV charging duration. These uncertainties are treated separately for each customer. A Java-based tool was built [6] to create different network configurations by varying the aforementioned variables. This tool is extended to include Distributed Generation (DG) from renewable sources, considering that the type and location of each DG installation are uncertain.

The extended tool was used to create different network configurations according to the variables mentioned above. For each generated case, synthetic data were used as inputs for the residential load and the DG profiles. The impacts on distribution transformer and cable loading, steady-state voltage and losses were recorded.

A smart charging function was added to the tool for controlling EV battery charging in order to minimise the impact on these constraints. The function simulates a type of centralised control where EV battery charging is coordinated, taking into consideration distribution network constraints and preferences of EV owners.

TABLE I: OPERATIONAL STATE RANGES FOR LV STUDIED PARAMETERS

Parameter	Nominal Rating	Operational State Range (p.u.)			References
		Normal	*Alert*	*Emergency*	
Transformer loading summer season	500 KVA	0-1	1-1.2	More than 1.2	[11,12]
Transformer loading winter season	500 KVA	0-1.2	1.2-1.4	More than 1.4	
185mm^2 cable loading	347 A	0-1	1-1.45 for less than 4 hours	1-1.45 for more than 4 hours or more than 1.45	[13]
Voltage	230V (1 phase)	0.95-1.09	0.94-0.95 and 1.09-1	Less than 0.94 and more than 1.1	[8]

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II. TECHNICAL CONSTRAINTS

LV networks in the UK have a nominal line to neutral voltage of 230V. The actual voltage should be within +10% and -6% from this value [8]. The operational limits of each studied constraint are categorized into normal, alert and emergency states, following the theory provided in [9]. Table I shows the range of each state for the different constraints. More details on the assumed values for each constraint are provided in [6]. The constraints studied in this research are steady state voltage, distribution transformer and cable thermal loadings. The 185mm^2 cable which connects the substation busbar with the 96 customer detailed feeder (marked with red in Fig. 1), was identified as the most vulnerable cable.

In the UK, system losses are typically 5% of the distributed energy [10]. This paper reports the line losses and the ratio of losses/energy delivered in the area serving 96 customers (see Fig. 1).

III. UK GENERIC DISTRIBUTION NETWORK

The radial LV network used in this paper was assessed by a number of Distribution Network Operators (DNOs) and considered as representative of urban UK distribution networks. Fig. 1 shows the schematic of the generic network. Details of the network parameters can be found in [14].

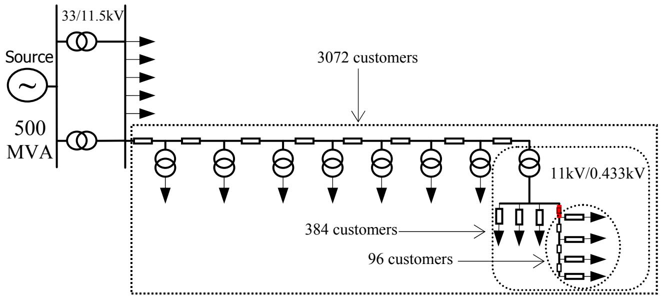

Fig. 1. UK Generic LV Distribution Network

IV. SYNTHETIC DATA

When an average daily profile is available, synthetic data can be generated by means of adding randomness [15]. This is done using a specific predefined pattern so that the resulting data seem realistic. Based on the available profiles, daily variations are applied as a random perturbation factor which is uniform for the whole day. Similarly, an hourly perturbation factor is applied. These factors are essentially noise which is added to the profiles. They are incorporated into the data by multiplying each half-hourly value of the profile with R:

$$R = 1 + S_d + S_h \qquad \text{Eq. (1)}$$

where

S_d is the daily perturbation factor and
S_h is the hourly perturbation factor.

Synthetic data generation was used to create a residential load and a micro-generation profile for each customer. Each profile was multiplied by a factor R, resulting from uniformly distributed random assignments of perturbation factors, with their maximum being 20% (daily) and 15% (hourly) according to [15].

V. TOOL INPUTS AND COMPUTATIONAL PROCEDURE

A. *Tool Inputs and 2030 Case Study Data*

The data used as inputs to the tool are (i) penetration levels for micro-generation and EVs, and (ii) load/micro-generation profiles for domestic residences. Projected EV and micro-generation penetration levels are utilised for 2030 based on previous studies [16]. The number of EVs and the micro-generation installations per 3,072 customers in the year 2030 is presented in Table II. Three penetration levels are used for EVs and two for micro-generation. The Microturbines, Fuel Cells and Stirling Engines are considered to be micro-CHP units, capable of producing heat at a Heat to Power Ratio (HPR) of 2.6; 1.4 and 5.0 respectively [17, 18].

TABLE II
PROJECTED MICRO-GENERATION AND EV PENETRATION LEVELS PER 3072 CUSTOMERS IN 2030

Component	Unit Power (kW)	Penetration (Units)	
		Low	High
Wind Turbines	2.5	32	88
Photovoltaics	1.5	16	48
Fuel Cell (Natural Gas)	3	24	81
Micro-turbine (Biogas)	3	16	32
Stirling Engine (Wood Pellets)	1.2	104	304
Total	-	***192 (6.25%)***	***544 (17.7%)***

Type of EV	Low	Medium	High
BEV	128	256	640
PHEV	256	768	1536
Total	***384 (12%)***	***1024 (33%)***	***2176 (70%)***

<u>Residential load profiles:</u> Data from [19] were scaled to the values of the specific model (from 0.16kVA to 1.3kVA per customer), provided by the Electricity Association. An annual increase of 1% from the publication year of the model was considered, according to UK DNO's estimations [20].

The amount of residential customers engaged with Economy 7 tariff was assumed to double among EV owners in 2030.

<u>Micro-generation Profiles</u>: Generation profiles for wind turbines and photovoltaics were drawn from [21], for average winter and summer days, in half-hour intervals. The micro-CHPs were assumed to be following the heat load, since heat storage was not considered. Daily heat load profiles for typical summer and winter days were drawn from [22].

<u>EV Charging Regimes</u>: In this research study the EVs were considered as loads. In order to create EV battery charging profiles, the EV charger rating as well as the occurrence and duration of each charging session were taken into account.

European Standards on EV conductive chargers (IEC 62196) are to be defined by the end of 2011 [23]. The present study assumed that (i) 10% of the BEV owners would use 32A three phase chargers, (ii) 20% would use 32A single phase chargers and (iii) the rest would use 13A single phase chargers. PHEV owners were assumed to use 13A single phase chargers.

Two charging modes were considered to simulate the charging behaviour; dumb and smart charging.

a) Dumb charging is distinguished into economy and uncontrolled charging. Economy charging was assumed to occur between 11 p.m. and 6 a.m., following a typical UK Economy 7 schedule. Uncontrolled charging denotes the case where customers plug-in their EVs in an uncontrolled manner. The starting time of uncontrolled charging is determined by the time when residential peak load occurs, presumably when commuters return home. The uncertainty of each customer's EV battery State of Charge (SOC) prior to the charging, was addressed by creating random charging duration for each EV owner.

The procedure of creating random charging regimes for each EV owner, as well as the EV battery and charger efficiencies, is given in [6] and [24]. The usable battery capacities are considered to be 28 kWh for BEVs and 7.2kWh for PHEVs [24].

b) In the smart charging mode it is assumed that the commuters will be able to choose the desired final SOC and the ending time of the charging session. This mode would allow the utility to control the charging of each battery according to localised constraints and commuter's preferences. Thus, it simulates a type of centralised control, for which an additional incentive would be given to the EV owner.

Each commuter who is being assigned this charging mode is given a random charging session start time, like in the uncontrolled mode. The starting time for the charging sessions of both charging modes was modelled as a normal distribution with its mean being the peak load time. A standard deviation of two hours was used. Based on the charger rating assigned to each commuter, a random charging duration and a SOC at the end of the session are produced. These two values were modelled to follow a uniform distribution.

B. Computational Procedure

Main Method: The tool allocates residential load and micro-generation profiles randomly to customers according to the penetration level. EVs are allocated to customers and the smart charging function is assigned to a pre-defined fraction of EVs. The charging profiles are created and the final profiles for each bus are computed. A Newton-Raphson load flow algorithm runs for each half-hourly time step and the results are recorded. The convergence criterion is tested [6] and the algorithm restarts or halts accordingly. The computational procedure is shown in Figure 2.

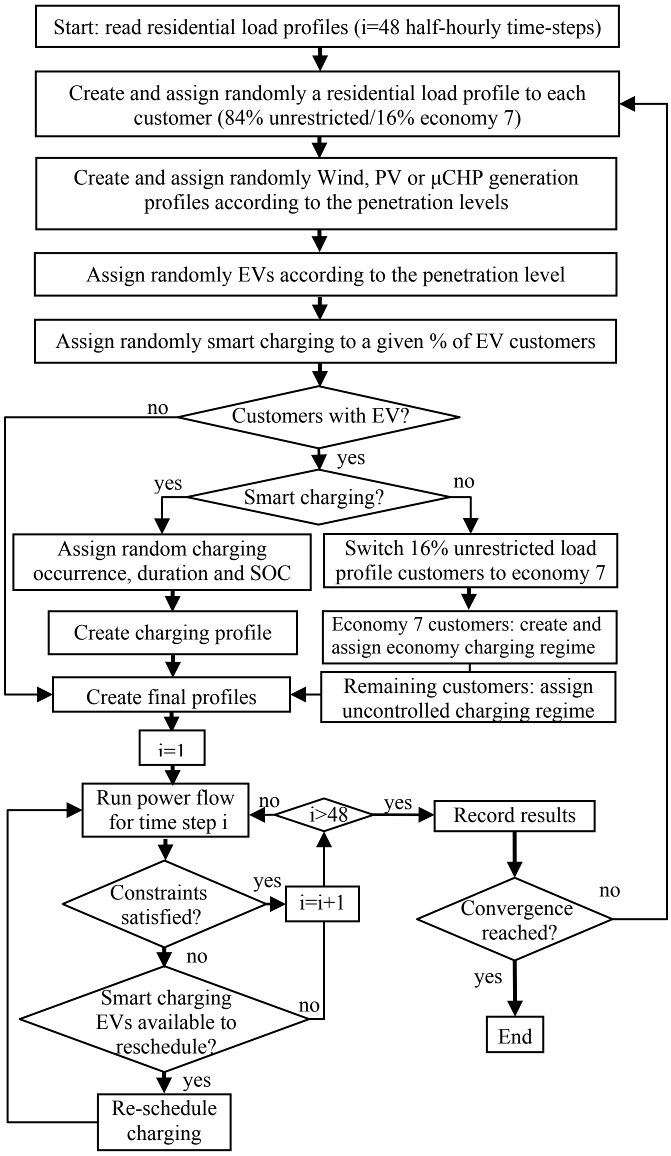

Fig. 2. The computational procedure

Centralised EV Charging Rescheduling: Several policies could be followed by a central controller with respect to the rescheduling of the EV charging. The central controller's priorities for rescheduling the charging of EVs will depend on: (i) the control structure, (ii) business model and (iii) level of intelligence of each control system asset.

Control strategies that could be followed include centralised and decentralised control. In a decentralised control strategy, the procedure for delaying or coordinating EV charging, could involve ageing of EV battery or electricity market price signals. In a more centralised control system, the central controller could prioritise the EVs whose services would be utilised, according to their network location or the frequency of use of their services.

In this research study, EV re-scheduling was prioritised according to the EV charger rating in a descending order. This means that the EVs utilising the charger with the highest power rating were rescheduled first. The criterion for this choice was the computational efficiency of the algorithm. The procedure of the smart charging rescheduling is explained as follows.

At the end of the load flow for the first time-step, a routine checks the results for voltages, transformer and cable thermal limits of the detailed microgrid (dotted area with 384 customers in Fig. 1). This is done according to the limits presented in Table I. If any constraint is found to be in alert or emergency state for the specific time-step, then an EV in smart charging mode is rescheduled according to the preferences of the user. The aim of the procedure is to check whether the desired SOC of the chosen EV may still be achieved, even by avoiding to charge at the specific time-step. If this is the case, the power flow re-runs for the same time-step and the checking routine is repeated. If the specific EV cannot be rescheduled, the next EV is checked. If there are no more EVs available for rescheduling or no constraints violated in the system after the inspection, the algorithm moves to the next time-step.

VI. Simulation Results and Discussion

The simulation results of 96 cases were recorded. These cases were created by varying the penetration levels of EVs and DG according to Table II. These levels were considered to reflect 2030 scenarios based on previous studies [16]. Smart charging levels were varied from 0% to 100% at 25% steps.

The results show that EV battery charging proves onerous for the system steady-state voltage. Fig. 3 shows the distribution of states for the voltage of the most remote busbar during a winter season. The increase of micro-generation sources and the control of EV charging via the smart charging function can reduce the voltage violations. For the case of low EV penetration, the wide application of smart charging among EV owners may prevent any voltage violation from taking place.

The 185mm^2 cable which connects the substation busbar to the 96 customers' feeder was found to be in emergency state for almost all 2030 winter season cases. The penetration of DG and the application of the smart charging for EVs showed only a slight improvement in the cable loading. However, the majority of operational states resulted in emergency and this could imply immediate consideration needs for the DNOs.

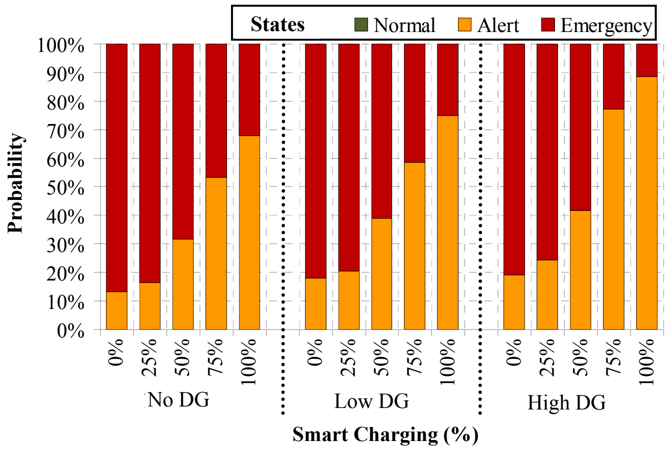

Fig. 4. Distribution transformer operational states (Low EV penetration).

The distribution transformer would be in alert operational state in 2030 for both projected DG penetration levels. EV battery charging would further increase the transformer loading, leading to emergency operational state. The wide application of smart charging for EVs (i.e. 100% smart charging) would reduce the probability of emergency state operation to approximately 30% for zero DG penetration and 10% for high DG penetration. Fig. 4 shows the transformer loading operational states for low EV penetration during a winter season.

Network losses would increase with EV battery charging since the energy required from the grid to charge the batteries would be greater. The simulation results show that electrical line losses were decreased by approximately 0.5% and 1% for low and high DG penetration levels respectively, compared to zero DG penetration.

The application of smart charging would further decrease power line losses by 1%. Fig. 5 shows the average daily power losses for all DG and EV penetration levels that occurred within the area of 96 customers. A column was added to the graph to illustrate the effect of 100% smart charging on losses for the high EV penetration scenario. The lines refer to the secondary vertical axis. This axis denotes the percentage of power line losses, relative to the grid imported energy to cover the respective load, in the 96 customers' area.

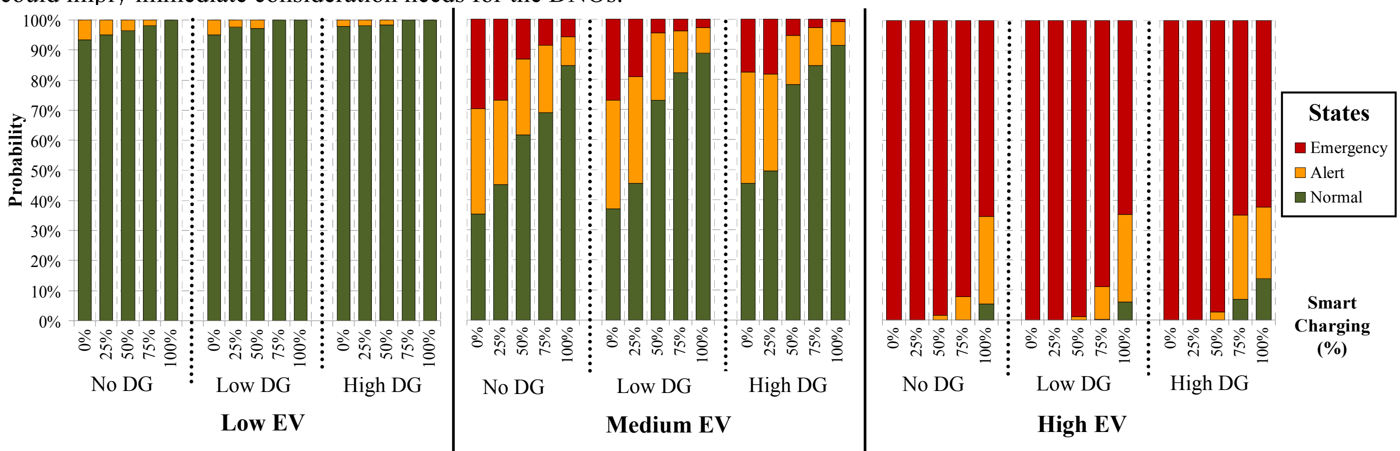

Fig. 3. Operational states for the steady-state voltage of the most remote customer

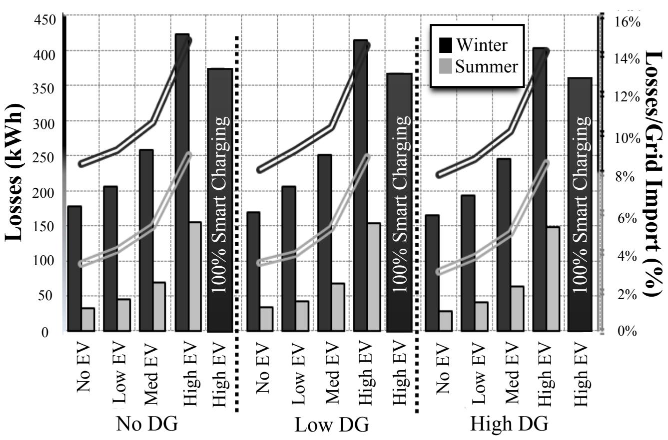

Fig. 5. Daily average power line losses in 96 customers area

VII. CONCLUSIONS AND FUTURE WORK

Future distribution networks are anticipated to incorporate Electric Vehicles and Distributed Generation. The integration of these new assets requires transformer and cable thermal loadings and steady-state voltage studies. A three-phase generic UK LV distribution network was used to conduct simulation studies based on sequential load flows. The inputs are (i) bus half-hourly profiles consisting of residential load, (ii) micro-generation and (iii) EV charging profiles. The uncertainties of residential loads and micro-generation power outputs were addressed by synthetic data generation. The uncertainties associated with EV battery charging were treated with a probabilistic approach. A control function based on a heuristic algorithm was created to simulate smart EV charging.

A case study for the year 2030 was built based on demand increase and forecasted EV and micro-generation penetration levels from the literature. The results showed that EV battery charging would prove onerous for the constraints studied. DG penetration would be able to provide support for EV battery charging but EV battery charging management would be necessary to minimise the impact in order to reach high levels of EV penetration. Future research will focus on the functionalities of such control to define a system structure and the level of intelligence of each system element.

REFERENCES

[1] P. Papadopoulos, N. Jenkins, L. M. Cipcigan and I. Grau, "Distribution networks with electric vehicles," 44th International Universities Power Engineering Conference, (UPEC 2009), 1-4 September 2009.

[2] J. A. Peças Lopes, F. J. Soares and P. M. Rocha Almeida, "Identifying Management Procedures to Deal with Connection of Electric Vehicles in the Grid", IEEE Bucharest Power Tech Conference, 2009.

[3] G. A. Putrus, P. Suwanapingkarl, D. Johnston, E. C. Bentley, and M.Narayana, "Impact of Electric Vehicles on Power Distribution Networks", 2009.

[4] K. Clement, E. Haesen, and J. Driesen, "Coordinated Charging of Multiple Plug-In Hybrid Electric Vehicles in Residential Distribution Grids", 2009.

[5] L. Kelly , A. Rowe, and P. Wild, "Probabilistic Modelling of the Impacts of Plug-in Electric Vehicles on Distribution Networks in British Columbia", Electrical Power and Energy Conference, 2009.

[6] P. Papadopoulos, S. Skarvelis-Kazakos, I. Grau, B. Awad, L. M. Cipcigan, N. Jenkins, Electric Vehicle Impact on Residential Distribution Networks, a Probabilistic Approach, UPEC, Cardiff, September 2010, in press.

[7] European Comission, "Mobile Energy Resources in Grids of Electricity", [Online], Available at: http://ev-merge.eu/

[8] Department of Trade and Industry, "The electricity safety, quality and continuity regulations". Stationary Office, October 2002, London, UK.

[9] P. Kundur, 'Power system stability and control', 1994.

[10] OFGEM, Electricity Distribution Loss Percentages by Distribution Network Operator (DNO) Area. [Online]. Available: http://www.ofgem.gov.uk/Networks/ElecDist/Documents1/Distribution%20Units%20and%20Loss%20Percentages%20Summary.pdf

[11] T., A. Short, "Electric Power Distribution Handbook", 2004.

[12] P. Abreu, "Design and Planning Framework for Underground Networks (And Associated HV/LV Distribution Substations) In EDF Energy's Three Distribution Networks (EPN, LPN And SPN)", 2005.

[13] G., F. Moore, "Electric Cables Handbook", 2006.

[14] S. Ingram, and S Probert, "The impact of small scale embedded generation on the operating parameters of distribution networks", P B Power, Department of Trade and Industry (DTI), 2003.

[15] T. Lambert, P. Gilman and P. Lilienthal, (2005), "Micropower system modeling with HOMER", Chapter in Integration of Alternative Sources of Energy, Farret FA, Simões MG, John Wiley & Sons, December 2005, ISBN 0471712329.

[16] I. Grau, S. Skarvelis-Kazakos, P. Papadopoulos, L. M. Cipcigan, and N. Jenkins, "Electric vehicles (EV) support for intentional islanding. A prediction for 2030". North American Power Symposium, 2009.

[17] N. D. Strachan, and A. E. Farrell, (2006), "Emissions from distributed vs. centralized generation: The importance of system performance." Energy Policy Vol. 34, No. 17, pp. 2677-2689.

[18] Carbon Trust, (2007), "Micro-CHP Accelerator", Interim Report, November 2007, Publication ID: CTC726

[19] UK Energy Research Centre, "Electricity user load profiles by profile class", 1997. [Online]: Available at: http://data.ukedc.rl.ac.uk/browse/edc/Electricity/LoadProfile/data

[20] S. Slater, M. Dolman, P. Taylor, P. Trichakis, and J. Shine, "Strategies for the uptake of electric vehicles and associated infrastructure implications", 2009.

[21] DTI Centre for Distributed Generation and Sustainable Electrical Energy, "United Kingdom Generic Distribution System (UKGDS)", http://www.sedg.ac.uk/ukgds.htm, last visited 26 Feb 2010.

[22] S. Abu-Sharkh, R.J. Arnold, J. Kohler, R. Li, T. Markvart, J.N. Ross, K. Steemers, P. Wilson, and R. Yao, (2006), "Can migrogrids make a major contribution to UK energy supply?", Renewable and Sustainable Energy Reviews, Vol. 10, No. 2, April 2006, pp. 78-127

[23] IEC 62196 Plugs, socket-outlets, vehicle couplers and vehicle inlets - Conductive charging of electric vehicles - Part 1: Charging of electric vehicles up to 250A a.c. and 400A d.c.

[24] P. Papadopoulos, O. Akizu, L. M. Cipcigan, N. Jenkins and E. Zabala, "Electricity demand with electric cars: Comparing GB and Spain", submitted for publication.