Local vs. Centralised Charging Strategies for Electric Vehicles in Low Voltage Distribution Systems

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***Abstract*—Controlled charging of electric vehicles offers a potential solution to accommodating large numbers of such vehicles on existing distribution networks without the need for widespread upgrading of network infrastructure. Here, a local control technique is proposed whereby individual electric vehicle charging units attempt to maximise their own charging rate for their vehicle while maintaining local network conditions within acceptable limits. Simulations are performed to demonstrate the benefits of the technique on a test distribution network. The results of the method are also compared to those from a centralised control method whereby EV charging is controlled by a central controller. The paper outlines the advantages and disadvantages of both strategies in terms of capacity utilisation and total energy delivered to charging EVs.**

***Index Terms*—linear programming, load flow analysis, optimisation methods, power distribution, road vehicle electric propulsion**

I. Introduction

THERE is growing interest in electric vehicle technology across the world, with many countries setting targets for the integration of electric vehicles (EVs) into their respective transportation sectors. The term "electric vehicle" can cover a number of technologies that employ electrical energy as a means of propulsion. These include battery electric vehicles, 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, in particular an electricity network.

Widespread implementation of plug-in EVs would lead to significant changes to the way in which distribution systems are planned and operated. Recent work in this area has sought to investigate the limitations from large numbers of EVs on network infrastructure in terms of increased loading, impacts on efficiency and loss of life for network assets [1]–[5]. The consensus from these studies is that existing distribution networks should be able to accommodate substantial penetration levels of EVs if the majority of charging is restricted to single-phase charging at off-peak times.

The introduction of advanced metering infrastructure (AMI) systems in residential housing, be it for real-time pricing or active demand side management, or both, will aid the control and predictability of the load patterns on residential networks. In order to accommodate large numbers of EVs in distribution systems, charging strategies could be implemented to control the rate at which individual EVs charge. Previous work has shown that by controlling the charge rates of EVs on a low voltage (LV) residential network, so as to deliver the maximum amount of power while maintaining the network within its acceptable operating limits, many more vehicles can be accommodated for charging than would be possible in an uncontrolled scenario [6].

In [7], quadratic and dynamic programming techniques are utilised to minimise the impact from EV charging on network losses and deviations from nominal voltage on residential networks. By controlling and optimising individual EV charging rates, network losses and voltage deviations are reduced for all penetration levels examined. The work described in [8] and [9] propose management strategies for EV charging/discharging in LV microgrids. By allowing network control devices to respond to voltage and frequency levels, it is shown that the EV load can enable LV microgrids to be operated in a stable manner. In [10], optimal charging strategies are developed whereby aggregated EV load can be used for network regulation purposes. A number of optimisation methods for determining the EV charging rates are examined. Depending on the particular algorithm used, the techniques were shown to provide significant benefits in terms of cost savings for the customer and aggregator, and flexibility for utilities accommodating variable renewable energy sources. The work described in [11] uses an estimation of distribution algorithm to schedule EV charging for large numbers of EVs in a parking deck. The method optimises the energy allocation to the EVs in real time while considering various constraints associated with EV battery limits and utility limits. The method compares favourably to other optimisation techniques in terms of total energy delivered upon departure of the EVs. In [12], the ability of a large number of EVs to smooth the load profile of residential networks is investigated. By controlling the bi-directional flow of energy to and from the EV batteries, it is demonstrated that EVs can supply power to meet residential load peaks while also creating more predictable load profiles.

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This work was conducted in the Electricity Research Centre, University College Dublin, Ireland, which is supported by the Commission for Energy Regulation, Bord Gáis Energy, Bord na Móna Energy, Cylon Controls, EirGrid, Electric Ireland, EPRI, ESB International, ESB Networks, Gaelectric, Intel, SSE Renewables, UTRC, and Viridian Power & Energy.

This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant Number 06/CP/E005.

Utilising EVs for the smoothing of load profiles is also shown to be beneficial in terms of accommodating renewable distributed generation.

This paper proposes a strategy for optimising the charging rates of EVs based on a local control charging (LCC) method. The objective of the strategy is to deliver the maximum amount of energy to the EVs while maintaining the network within acceptable operating limits. The LCC method allows the optimal charging rates of the EVs to be determined individually based solely on local network conditions and their battery state of charge. This paper investigates the potential advantages and disadvantages of the LCC strategy in terms of network capacity utilisation and total energy delivered to EVs. The results are compared to those of a centralised control charging (CCC) method whereby a single controller manages the charging rates of all the EVs on the network simultaneously [6].

The methodology for this work is presented in Section II. Section III describes the modelling of the test network, the residential load and the electricity demand profiles of the EVs. Results and discussion for a sample charging period are presented in Section IV along with generalised results for a wide range of network scenarios. Conclusions are presented in Section V.

II. Methodology

A. Assumptions

In order to implement any type of active control at the LV distribution system level, it is assumed that EV charging units with load control capability are present in each household with an EV present. AMI, which is also assumed to be present in each household, enables time-of-day electricity tariffs which incentivise customers to avoid the more expensive peak load time of day. Each EV can charge at any rate between zero and the charger's maximum rated charge, subject to certain restrictions, which are outlined later in this section. It is assumed that each of the EV charging units on the network have the same charging capabilities. The ability to vary the charge rate of individual EVs in a continuous manner for use in optimal charging strategies has been studied previously [7], [10], [13]. While the possibility exists for fast, 3-phase charging, it is assumed that each EV will be connected to the network via a standard single-phase AC connection. Although the concept of vehicle-to-grid for local system support or otherwise exists [8], [10], [14], bi-directional flow of electricity to and from an EV battery is not considered in this work. For the CCC method, it is assumed that the load control capability of the EV charging units can be utilised by the distribution system operator (DSO), or a third-party controller, from a remote location.

B. Local Control Charging

Local control charging of EVs is achieved by each individual EV charging unit maximising the charge rate of their connected EV, subject to the voltage at its own customer point of connection (CPOC) and the loading of its own single-phase service cable. For each distributed control charging unit, the sensitivity of the CPOC voltage and service cable loading to the addition of EV load at its charger unit is predetermined and is not updated at each time step (Section II-D). With the predetermined sensitivity value, along with information about the instantaneous voltage at the CPOC and loading of the service cable, the charging unit maximises the rate of charge of the EV without exceeding either the local voltage or single-phase loading limits.

The objective of the charging units in the LCC strategy is to maximise the amount of power delivered to their individual EV at each 15 minute time step, subject to certain constraints. Each charging unit aims to maximise its own charge rate and cannot communicate with any other charger unit on the feeder. The process is performed using the linear programming tool in [17] and the optimisation occurs for each EV connected to the feeder and available for charging. The optimisation is calculated at each time step *t*. In this case, the objective function, F_{LCC}, is given as

$$F_{\text{LCC}} = P_{\text{EV}} x \tag{1}$$

where P_{EV} is the power delivered. It is assumed that P_{EV} is a continuous control variable that can vary between 0 kW and the maximum power output of the charger. x is zero when an EV is not connected at the CPOC or the EV battery is fully charged, while x equals one when the EV at the CPOC is connected and the EV battery is not fully charged.

C. Constraints

While each of the charging units has the ability to vary their output in a continuous manner, the charging rate limits are defined in (2), where $P_{\text{EV}_{\text{max}}}$ is the rated output of each charging unit.

$$0 \leq P_{\text{EV}} \leq P_{\text{EV}_{max}} \tag{2}$$

In order to avoid large variations in the charging rate over consecutive time steps, which is undesirable for current battery technology [15], a rate of change constraint is also imposed (3).

$$P_{\text{EV}}{}^{t-1} - \Delta \ \leq \ P_{\text{EV}}{}^{t} \ \leq \ P_{\text{EV}}{}^{t-1} + \Delta \tag{3}$$

Here, *t* is the current time step and Δ is a defined limit, in kW, by which the charging rate can vary, compared to the charging rate at the previous time step, excluding on/off transitions.

For the LCC method, the EV charger unit has the capability to monitor the voltage at its own CPOC and the loading on the service cable supplying the customer residence only. The addition of EV loads, for the most part, will cause the voltage at various points of the network to drop. The extent of the voltage drop can vary depending on a number of factors, which include the location of the EV on the network and the rate of charge. The voltage at each CPOC must be maintained within the rated voltage range specified for the network, (4).

$$V_{min} \leq V_{\text{CPOC}} \leq V_{max} \tag{4}$$

Here, V_{CPOC} (V) is the voltage at the CPOC, while V_{min} and V_{max} are the minimum and maximum allowable network voltage levels respectively. The thermal loading of the service cable refers to the total current flowing through the cable. This constraint is summarised in (5).

$$L_{\text{SC}} \leq L_{\text{SC}_{max}} \tag{5}$$

Here, L_{SC} is the thermal loading of the service cable and $L_{\text{SC}_{max}}$ is the current rating for the fuse at the CPOC for the household.

D. Network Sensitivities

As stated in Section II-B, for the LCC method, the network voltage and loading sensitivities to the addition of EV load are predetermined. Only one set of sensitivities is used for all time steps, which allows the charging unit at each household to determine an optimal charge rate without the need to calculate a new set of sensitivities at each time step. However, these sensitivity values cannot be expected to match the constantly varying load on the feeder. In order to determine the set of voltage and loading sensitivities for the LCC method, a series of unbalanced, 3-phase load flow calculations are performed on the test network using power system simulation software [16]. These load flow calculations determine the change in voltage and loading levels at all points on the network subject to the addition of EV load at each CPOC. In order to model the expected residential load during charging periods, each household is assigned a 2 kW load, which approximates the maximum average household demand over all time steps in winter. The sensitivity values for the voltage and loading assigned to a charging unit are the summation of all the voltage and loading sensitivities at all other CPOCs on the feeder respectively. This takes account of the impact that multiple EV loads, charging simultaneously, can have on a particular node and service cable on the feeder. This fixed sensitivity value is used in conjunction with the CPOC voltage and service cable loading measurements at each time step in order to determine the optimal charging rate for the EV. The constraint equations for the CPOC voltage and service cable loading are summarised as,

$$V_{min} \leq V_{init} + \mu P_{\text{EV}} \leq V_{max} \tag{6}$$

$$L_{\text{SC}_{init}} + \beta P_{\text{EV}} \leq L_{\text{SC}_{max}} \tag{7}$$

where, in (6), V_{init} is the initial voltage at the CPOC. μ (V/kW) is the summation of the voltage sensitivities at each CPOC due to power demanded by that EV. For (7), $L_{\text{SC}_{init}}$ is the initial loading on the service cable supplying the EV, and β (A/kW) is the summation of the loading sensitivities for each service cable due to power demanded by that EV.

E. Centralised Control

Centralised control of EV charging involves monitoring the voltage at each CPOC, the thermal loading of each household's single-phase service cable, the loading of the LV transformer and the 3-phase mains cable supplying the feeder, and also the battery state of charge for each connected EV. This information is sent to a centralised controller which incorporates additional network information to determine dispatch signals at each time step for the individual EV charger units accordingly. The sensitivities of the voltage and thermal loading of the network to EV load are calculated in advance for each time step. The centralised controller is also aware of all network voltages and line flows, which allows for a more accurate insight into the instantaneous network condition than is possible with the local control method. The controller then optimises the charge rate of each vehicle in order to deliver the maximum amount of power delivered to all EVs on the feeder, and thereby making best use of the network capacity. The process occurs at each time step and is independent of all other time steps with the exception of the rate of change of charge constraint (3).

The objective function for the centralised control method, F_{CCC}, is given by

$$F_{\text{CCC}} = \sum_{i=1}^{N} \left(1 - \left(\frac{\text{BSOC}_i}{\text{BSOC}_{max_i}}\right)\right) P_{\text{EV}_i} x_i \tag{8}$$

where N is the number of customers being served by the network, and P_{EV_i} is the power delivered, measured in kW, to the EV connected at the *i*th CPOC. x_i is zero when an EV is not connected at the *i*th CPOC or the EV battery is fully charged, while x_i equals one when the EV at the *i*th CPOC is connected and the EV battery is less than fully charged. BSOC_i is the current battery state of charge (kWh) for the EV connected at the *i*th CPOC and BSOC_{max_i} is the maximum battery capacity of that EV.

In (8), the objective function is weighted according to the current BSOC of each individual EV. This weighting provides a more even distribution of energy to charging EVs and prioritises EVs with a low BSOC [6].

The centralised control charging technique considers the same constraints as the local control method (i.e. (2),(3),(4) and (5)), along with constraints ensuring that the rated loading of the network transformer and the mains cable supplying the feeder from the transformer are not exceeded. It is assumed that the necessary monitoring and communication equipment is installed on the feeder and that the data collected, along with the data from the AMI of the customers, can be utilised in determining the optimal charging rates for the EVs on the feeder. A more detailed description of the method and constraints for the centralised control method can be found in [6].

III. Simulation Data

A. Distribution Network

The test network is based on a LV residential distribution feeder in a suburban area of Dublin, Ireland. A simplified representation of the feeder is given in Fig. 1. In the actual test feeder, each household, EV and service cable are modelled separately. The model incorporates a 400 kVA, 10/0.4 kV step-down transformer supplying a feeder of 74 residential customers through 432 m of 3-phase mains cables and 2.16 km of single-phase service cables. A lumped load model, representing a similar number of residential customer loads with no EV loads, is included to represent another feeder being supplied from the same transformer.

In Ireland, the LV distribution network is operated at a nominal voltage of 230/400 V with a voltage range tolerance of

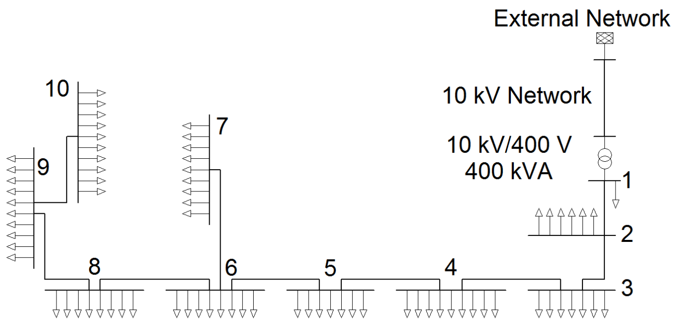

Fig. 1. Single line diagram of test network.

+/-10% [18]. The transformer modelled here does not have any tap-changing capability, which is typical of LV transformers in Ireland. As such, the medium voltage (MV) network supplying the LV transformer is included in the model as an equivalent impedance in order to take account of the voltage drop at this network level. The MV network is modelled such that at maximum residential load (with no EV charging) the voltage at all points of the network does not exceed -10% of nominal. The voltage at the sending end of the MV network is set at 1.05 pu. Specifications for the network model components were supplied by Electricity Supply Board (ESB) Networks, who are the DSO in the Republic of Ireland.

B. Residential Customer Load Modelling

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. These profiles were subject to time-of-day pricing whereby the cheaper, off-peak tariff begins at 11 pm each day and ends at 8 am the following day. Different electricity demand profiles were randomly assigned to each of the houses in the test network. In order to confirm that these load profiles portrayed an accurate representation of the power demanded by a real distribution feeder, the coincidence factor of the test network was determined. The coincidence factor is defined as the ratio of the maximum diversified demand divided by the maximum non-coincidental demand. From assessing the yearly load profiles for each of the households on the network, the coincidence factor was found to be 0.36, which compares favourably with networks serving a similar number of customers [19]. For modelling purposes, the power factor for each household load is set at 0.95 inductive. The load is modelled as a combination of 50% constant power (P) and 50% constant impedance (Z).

C. Electric Vehicle Load Modelling

It is assumed that each EV is connected at the same CPOC as the household load through a single-phase connection. Charging profiles for EVs can vary depending on battery type, charging equipment and the electricity supply network. For this work, all EV batteries are modelled with a capacity of 20 kWh. The EV charging equipment is assumed to have a maximum charging rate of 4 kW with a 90% efficiency rating. The charging rate of 4 kW is appropriate in terms of the power delivery capabilities of existing LV distribution networks in Ireland [18]. The EV batteries are modelled as constant power loads at unity power factor.

D. Time Periods for Investigation

1) Sample 24-hour Period: In order to demonstrate each of the charging strategies, a sample 24-hour time period within the one year period of residential load data was chosen. The time period selected is from 12 noon to 12 noon the following day and spans two weekdays in January. Due to the assumption that all customers are subject to a time-of-day tariff scheme, a large residential demand is experienced on the feeder once the cheaper off-peak period begins. The maximum demand on the feeder during this period is 270 kW.

In both cases, a 50% penetration of EVs on the feeder was examined, which means that 37 of the 74 households had exactly one EV charging at certain stages of the 24-hour period. While a 50% penetration of EVs on a distribution feeder may not be experienced for many years to come, it was deemed appropriate to examine such a scenario in order to fully capture the benefits of controlled charging strategies compared to uncontrolled charging. For the simulations, the EVs were allocated to the network in a random manner and the locations remained fixed for each of the charging strategy cases examined. The potential combined maximum demand from a 50% penetration of EVs is 148 kW. EV usage data was obtained from DSO led vehicle trials in order to determine a plausible range of connection times, durations of connection, and initial BSOC levels for the EVs in the simulations [20]. Based on this data, the connection time for each EV is randomly assigned within a time frame of +/-3 hours of 11 pm, which is the start of the off-peak period. The duration of connection for each EV is also randomly assigned, whereby a vehicle remains connected for anywhere between 6 and 15 hours. Each EV is also assigned an initial BSOC, independent of the connection time, at the beginning of the charge period, determined as a random value between 0% and 75% of the maximum battery capacity of 20 kWh, which ensures that each EV has a charge requirement of at least 25% of their battery capacity upon connection. The distribution of the initial BSOC for each EV is shown in Fig. 2. Table I shows the breakdown of EVs allocated on the feeder along with the total energy requirement of these vehicles on a phase by phase basis.

TABLE I
INITIAL EV CONDITIONS

	Number of EVs	**Combined Battery Capacity (kWh)**	**Combined Initial BSOC (kWh)**	**Total Energy Required (kWh)**
Phase a	12	240	86	154
Phase b	13	260	84	176
Phase c	12	240	53	187
Total	37	740	223	517

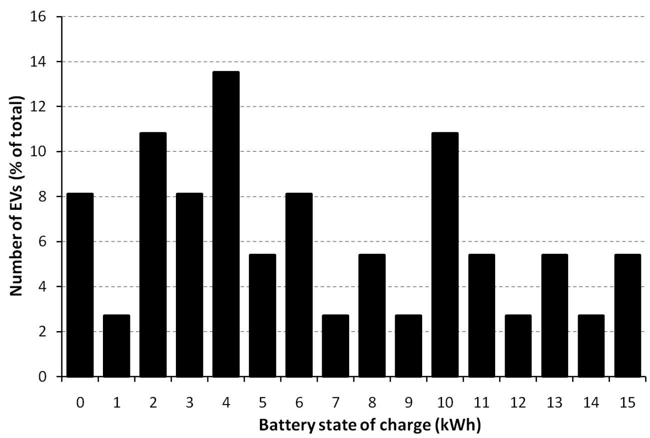

Fig. 2. Distribution of the initial BSOC for EVs.

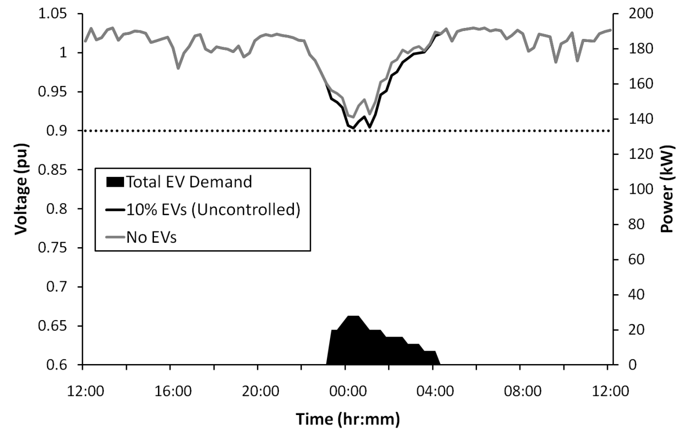

Fig. 3. Lowest CPOC voltage for base case and uncontrolled charging case, including the power demand from the EVs for the uncontrolled case.

2) Stochastic Scenario Analysis: The charging period identified above examines the LCC and CCC optimisation techniques for a specific network scenario. In order to investigate a wider range of scenarios, a stochastic tool, similar to one developed in [21], was used to generate different residential load scenarios with probabilistic conditions for varying residential load, EV location, initial BSOC and duration of connection.

Probability distribution functions (PDFs) for the household load were created based on the residential load data provided by the DSO, with PDFs for low, medium and high use customers. 15-minute household load profiles were then generated for each house for a 24-hour period from 12 noon on a winter weekday to 12 noon the following day, similar to the example 24-hour period. At the beginning of each 24-hour period the EV locations on the network were randomly selected with each EV then assigned an initial BSOC and duration of connection time. The duration of connection is randomly determined between 6-15 hours. The load model and power factor for both the residential and EV load remain the same as for the example 24-hour period analysis.

IV. Results and Discussion

Both controlled charging strategies are tested for the sample 24-hour period, with the results compared to cases with no EVs charging and with uncontrolled EV charging.

A. Uncontrolled EV Charging

In a scenario where no active control of EV charging is present, an EV, once connected, will charge at a maximum rate of 4 kW until it reaches a full BSOC. With distribution networks not rated to accommodate large penetrations of this type of load, a limit on the number of EVs allowed would have to be put in place to ensure that the network always remains within acceptable operating limits.

For the purposes of comparison, an example uncontrolled charging scenario was created whereby there is a limit to the number of EVs that are allowed to charge simultaneously. This number was determined by incrementally adding EVs, charging at their maximum rate of charge, to the feeder up to the point before the feeder exceeds an allowable operating limit. This test was performed with the residential load at the maximum expected demand for the example 24-hour period. For the test network utilised in this work, the predetermined number of EVs that could be allowed to charge in an uncontrolled scenario was found to be 7 ($\approx$ 10% of households).

Fig. 3 shows a profile of the lowest recorded CPOC voltage on the feeder for each time step for both the base case with no EVs and an uncontrolled case with a 10% penetration level. The total power delivered to the EVs at each time step is also shown. EV charging is assumed to commence once the off-peak period begins (i.e. 11 pm), although a number of EVs connect after this time also. As the figure shows, the introduction of EV charging during this time period pushes the lowest CPOC voltage towards the lower acceptable limit. Any further increase in the number of charging EVs at the beginning of the off-peak time period would likely result in the lower voltage limit being exceeded. The amount of energy delivered to the EVs in this scenario was 80.1 kWh.

B. Controlled EV Charging

The LCC method described in Section II is employed to optimise the charging rates of the EVs connected to the network. The rate at which each EV charges is now optimised individually in order to deliver the maximum power to the EVs while maintaining the voltage and service cable loading within acceptable operating limits for each time step. At the beginning of the charging period, the total energy required to return all EVs to 100% BSOC is 517 kWh. For the optimisation process, the lower voltage limit is set at 0.92 pu, which allows for a margin of safety with respect to the lower voltage limit (0.9 pu) defined in the Irish distribution network code [18]. This ensures that any unexpected short term variations in the demand will not cause the network to exceed its operating limits. The maximum variation allowable for the rate of charge between time steps, i.e. Δ in (3), is set at 1 kW for both control strategies. Values for the voltage sensitivities, μ in (6), were calculated to be in the range -0.02 to -0.045 V/kW. CPOCs located at the extremities of the feeder were found to be more sensitive to the addition of EV load than those located near

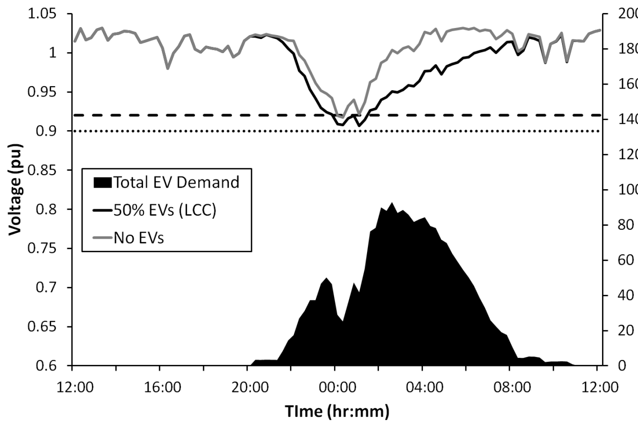

Fig. 4. Lowest CPOC voltage for base case and local control charging case, including the associated power demand from the EVs.

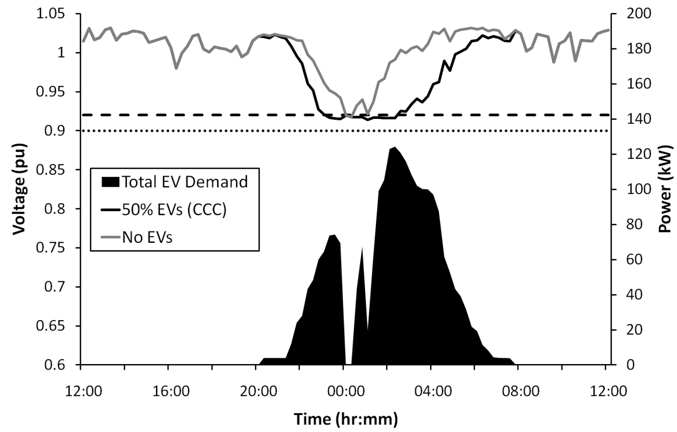

Fig. 5. Lowest CPOC voltage for base case and centralised control charging case, including the associated power demand from the EVs.

the start of the feeder. This characteristic is to be expected of a radial feeder. The loading sensitivities, β in (7), of the single-phase service cables were calculated to be in the range 8.2 to 8.7 A/kW.

The sample 24-hour time period is tested utilising the controlled charging method for an EV penetration level of 50%. Fig. 4 shows the lowest recorded CPOC voltage on the feeder for the base case and the LCC case, and shows that the control method has maintained the lowest voltage above the lower voltage limit of 0.9 pu. The method has achieved this by curtailing EV charging during periods of high residential demand and shifting it to a later stage of the night. However, due to the inability of individual charging units to know the network conditions at the other CPOCs on the network, each unit is unaware of how many EVs are charging at the same time step. This can potentially lead to network conditions exceeding values determined by the individual charger units in their optimisation calculations. An example of this can be seen in Fig. 4, where the lowest CPOC voltage has reached a value closer to the network limit of 0.9 pu, rather than the specified limit of 0.92 pu. At the following time step, individual charger units recognise that a limit has been exceeded and automatically attempt to rectify the situation by adjusting their charging rate accordingly.

Fig. 5 shows the results for the lowest CPOC voltage recorded for the case employing the centralised control method. When compared to the LCC method, it can be seen that the centralised control technique results in the lowest recorded CPOC being much tighter to the specified voltage limit than in the local control case. Due to the calculation of a new set of sensitivities and knowledge of current network conditions at each time step, the network controller has a much greater insight to the condition of the network at all CPOCs. This allows for a far more accurate dispatch of EV charge rates, resulting in more charge being delivered to the EVs while maintaining acceptable network operating conditions. An example of this can be seen in the EV demand profile for both methods. In Fig. 4, even though the base case lowest voltage is already at the specified lower limit just after midnight, the local control technique leads to some EVs requesting charge, which results in a further voltage drop. At the same instant, using the centralised control technique, the controller switches off all EV charging on the network until the lowest base case voltage increases above the specified limit.

The centralised control method's ability to update the set of sensitivities and measure all network conditions at each time step allows it to deliver the maximum amount of power to the EVs, which results in the network capacity being utilised to the fullest extent at each time step. However, in the local control case the sensitivities are fixed, which results in less power being dispatched to the EVs even though the network is not at any of the specified limits. This results in the LCC method taking longer to charge all of the EVs, as shown in Fig. 6, where the black area represents the electricity demand from the EVs. In some cases, this can result in EVs finishing their charge period with less than 100% BSOC due to the charger units not utilising the network capacity to its fullest. For both methods, the BSOC upon disconnection from the network is shown in Fig. 7. It can be seen that the local control case results in 3 of the 37 EVs having a final BSOC of less than 100%, with the lowest being 90%. Because the centralised control method can deliver more power earlier in the charging period it results in all 37 EVs having a full BSOC by the end of the period. Details of the total energy delivered to the EVs for both control charging methods are given in Table II.

TABLE II
TOTAL ENERGY DELIVERED TO EV BATTERIES

	Total Energy Delivered (kWh)	**% Energy Requirement (for 50% EVs)**
10% EVs (Uncontrolled)	80.1	15.5
50% EVs (LCC)	513	99.2
50% EVs (CCC)	517	100

For both of the methods tested, the lowest CPOC voltage was found to be the binding constraint for the optimisation. Fig. 8 shows the greatest loading for all service cables at each time step. While the service cable loading is considered by

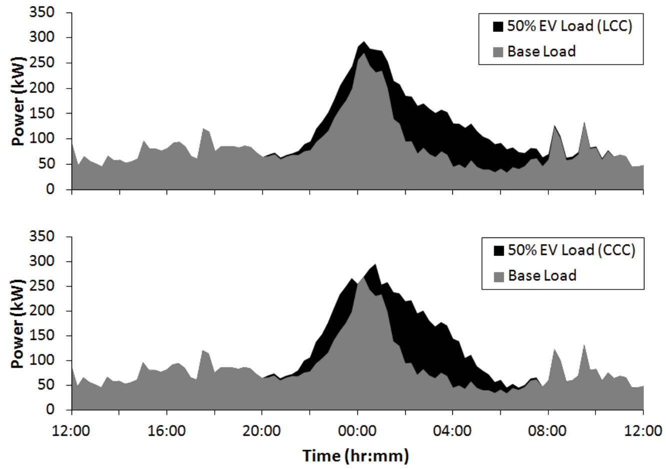

Fig. 6. Network demand profiles for the local control and centralised control charging scenarios.

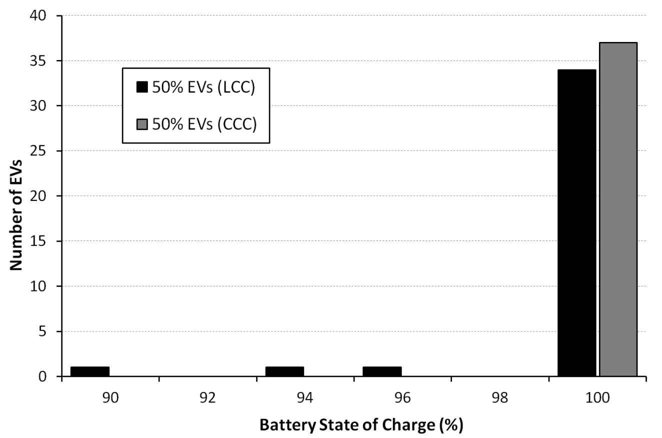

Fig. 7. Final BSOC for EVs for local and centralised control charging scenarios.

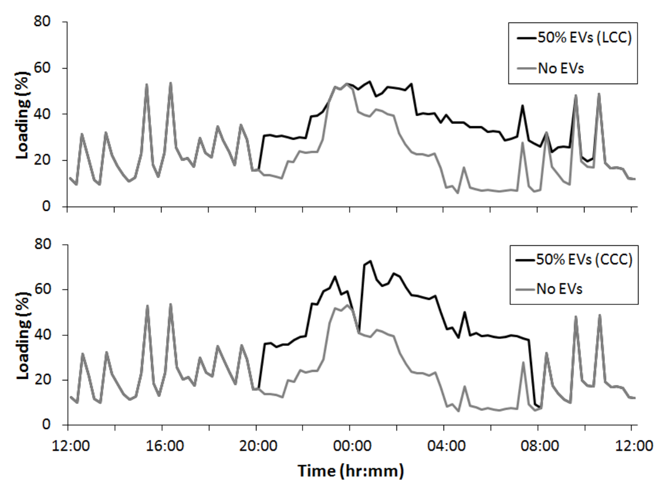

Fig. 8. Loading of service cable with greatest loading for each time step for the local control and centralised control charging scenarios.

both methods it is clear that it is never a binding constraint for the 24-hour period examined.

The CCC technique also considers the loading on the network transformer and the loading on the 3-phase mains cable supplying the feeder from the transformer. For the 24-hour period examined here, neither the transformer nor the mains cable loading are ever the binding constraint, as shown in Table III.

TABLE III
MAXIMUM NETWORK COMPONENT LOADING

	Transformer (%)	Mains Cable Phase a (%)	Mains Cable Phase b (%)	Mains Cable Phase c (%)
No EVs	75.7	55.2	37.1	53.6
10% EVs	81.9	59.4	52.1	57.8
50% EVs (LCC)	82.1	61.8	55.5	69.3
50% EVs (CCC)	80.1	68.9	64.0	71.5

Network losses as a percentage of the total energy delivered to the network over the 24-hour period were also recorded. The increased demand from EV charging causes the losses ratio to increase slightly for all cases compared to the base case (1.1%). For the 10% EV penetration with uncontrolled charging, the losses ratio was found to be 1.3%. The local control case (1.8%) incurs less losses on the network when compared to the centralised case (2.1%) but has delivered less energy to the EVs over the charging period.

C. Stochastic Scenario Analysis

A stochastic analysis of both charging strategies was performed in order to provide insight into operation of the optimisation process while accounting for the variability and uncertainties associated with EV charging, as described in Section III-D2. Each of the charging techniques were simulated on the test network for 300 distinct 24-hour periods (i.e. 28,800 time steps) during winter.

Fig. 9 shows the distribution of measured voltages for all CPOCs over all charging periods for the scenario with no EVs on the network and the scenarios for both controlled charging methods. There is a significant increase in the frequency of voltage levels nearer to the specified lower voltage limit (0.92 pu), with a small increase in the number of occurrences below this limit for both controlled charging methods. There are also more occurrences, using the CCC method, when the lowest CPOC voltage is at the specified limit, which demonstrates better utilisation of the network capacity. As explained in Section IV-B, this is due to the LCC method operating on a fixed set of sensitivity values and utilising local network information only, as opposed to the CCC method which updates the sensitivities at each time step and has exact knowledge of all network voltages and line flows.

The distribution of thermal loading levels measured on each of the single-phase service cables is shown in Fig. 10. For the majority of recorded values the loading is below 60% of the rating. The service cable loading is only a binding constraint for a very small fraction of the measured samples (i.e. less than 0.01%).

Finally, the distribution of the final BSOC for all the EVs for each charging period is shown in Fig. 11. The LCC method

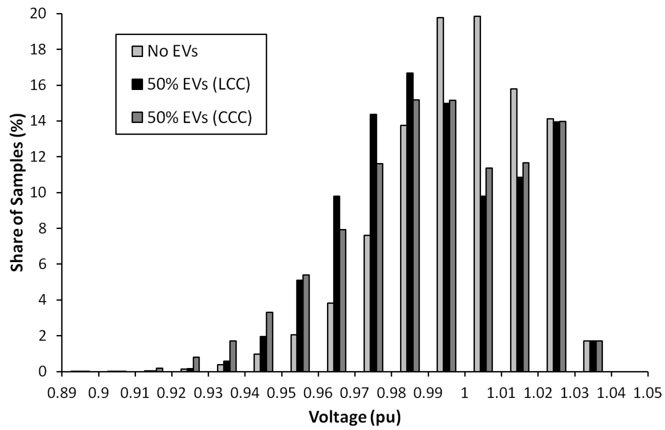

Fig. 9. Distribution of measured voltages at network CPOCs.

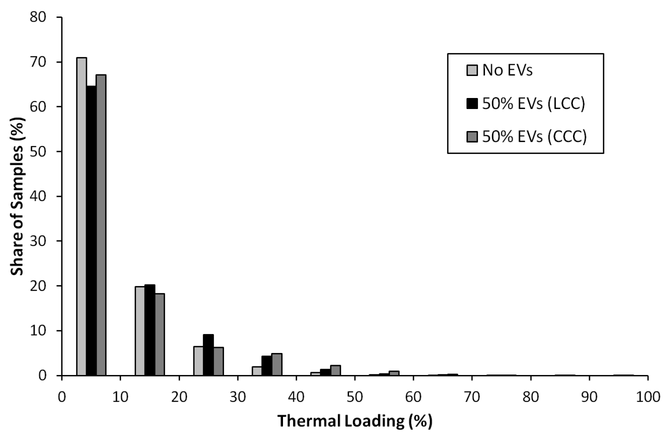

Fig. 10. Distribution of measured thermal loading levels of single-phase service cables.

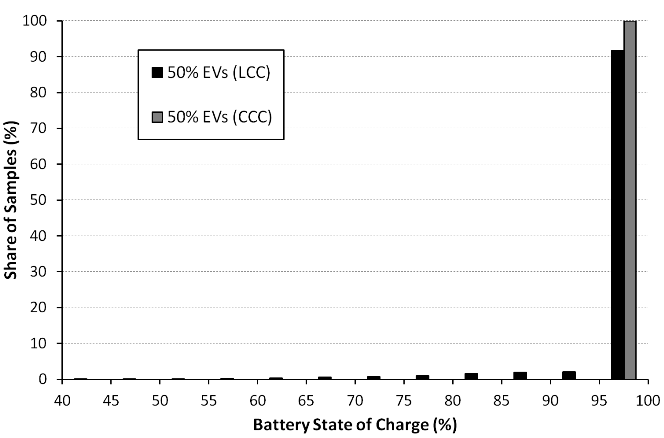

Fig. 11. Distribution of final BSOC levels for all charging periods.

resulted in over 90% of all final BSOC values being within 95-100%, with 97% of all values above 80%. For each of the CCC method charging periods, 100% of the final BSOC values were found to be within 95-100% of the maximum capacity.

V. Conclusion

This work has demonstrated the benefits of controlled charging for a high penetration of EVs charging on a LV network. A local control method was proposed whereby each individual EV charger maximises the charging rate of its EV while maintaining the CPOC voltage and service cable loading within acceptable limits. The method was tested on a LV test network and the results were compared to those employing a centralised control method.

The results indicate that the local control method allows a far greater penetration of EV charging on a feeder than that which could be accommodated with uncontrolled charging. While the technique can deliver a similar amount of energy to the EVs within a certain time period when compared to the centralised control method, it is not as capable at maintaining network parameters within specified limits and may require larger safety margins. However, introducing a number of predefined sets of sensitivities, each calculated based on the expected residential load for a given scenario (e.g. day/night, weekday/weekend, seasonal, etc.), could improve the performance of the local control method.

The network and communications infrastructure required to implement the local control method would be far less than that required for the centralised control case. Individual controllers would also be able to act independently and not be reliant on external controller signals in order to operate. As such, investing in a centralised control technique may not be required until very high penetrations of EVs on LV networks become a reality. With the introduction of AMI, a local control technique may be sufficient for accommodating initial penetrations of EV charging while maintaining network limits within the desired operating regions.

A summary of the advantages and disadvantages for both the LCC and CCC methods is given as follows:

Local Control Charging

Advantages:
· Minimal communications infrastructure required
· Sufficient for lower EV penetration levels
Disadvantages:
· No communication links to rest of network
· Larger safety margin required to maintain operating limits

Centralised Control Charging

Advantages:
· Real time insight into operating conditions at all points on network
· Better utilisation of network capacity
· Option to include BSOC weighting
Disadvantages:
· Requires significant communications infrastructure across network
· Requires 3rd party to control charging rates

Acknowledgment

The authors would like to acknowledge ESB Networks for providing the necessary data to perform this work. Thanks are also due to Jason Taylor of EPRI.

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