Smart charging for electric vehicles to minimize charging cost

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Abstract

This paper assumes a smart grid framework where the driving patterns for electric vehicles are known, time variations in electricity prices are communicated to householders, and data on voltage variation throughout the distribution system is available. Based on this information an aggregator with access to this data can be employed to minimize EV owner charging costs whilst maintaining acceptable distribution system voltages. In this study EV charging is assumed to take place only in the home. A single-phase LV distribution network is investigated where the local EV penetration level is assumed to be 100%. EV use patterns have been extracted from the UK Time of Use Survey data with 10-minute resolution and the domestic base load is generated from an existing public domain model. Apart from the so-called real time price signal, which is derived from the electricity system wholesale price, the cost of battery degradation is also considered in the optimal scheduling of EV charging. A simple and effective heuristic method is proposed to minimize the EV charging cost whilst satisfying the requirement of state of charge for the EV battery. A simulation in OpenDSS over a period of 24 hours has been implemented, taking care of the network constraints for voltage level at the customer connection points. The optimization results are compared with those obtained using dynamic optimal power flow.

Keywords

Electric vehicles, real time price signal, cost minimization, dynamic optimal power flow.

Introduction

The global target to achieve decarbonisation together with future limitations in fossil fuel resources has resulted in an increasing interest in electric vehicles (EV). Significant growth in EV usage will place significant demands on the power system. The additional power demand due to uncontrolled residential EV charging during weekdays coincides almost exactly with the daily load peak in the early evening, [1], and this will stress the distribution power system to an unacceptable extent as the number of EVs increases. Smart charging of EVs has the potential to mitigate these problems by shifting the charging load to a low demand period; this has the added benefit of reducing the EV charging cost to the vehicle owner.

A joint optimal power flow (OPF)-EV charging optimization problem is presented in [2], where the optimal EV charging is characterised as a valley-filling target. Both offline and online algorithms are proposed here, and the performance of the online algorithms is near optimal based on the offline valley-filling profiles. To improve power system asset utilization, the EV charging power in [3] is controlled to minimize the deviation of the instantaneous load from the average daily demand. Actions proposed in both [2] and [3]

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would have a direct effect on smoothing the daily demand curve and therefore also the voltage profile.

Richardson et al., [4], focus more on the primary function for EVs as transportation by maximizing the power delivery to EVs during the available charging period while operating within the network limits. Here linear network sensitivity is assumed between the network operation parameters, including nodal voltage and line thermal loading, and the addition of EV loads.

Three smart charging algorithms including price based, load based and regulation participation based are proposed in [5] to maximize the profits to the aggregator. This work assumes that aggregator income comes from both power delivery to the EVs and regulation service provision, and as a result the aggregator would try to arrange as much EV charging as possible. Reference [6] also focuses on the aggregator by minimizing the deviation between the energy bought in by the aggregator and the energy consumed by EVs at each time step, using EV charging power control. On completion of scheduling of the EV charging, any power network violations are then resolved by iteratively decreasing the load on the problematic buses in 10% steps.

A rolling optimization approach is proposed in [7], in which a moving window of length 12 hours achieves the local minimization of EV charging cost and then advances into the next period, sliding with a step of 30 minutes, until the simulation period of 24 hours is completed. Here the load flow is performed via an inverted Jacobian matrix, which relates the current change in each specific node to the voltage changes in all the nodes including the one under consideration. Mocci et al. introduces a master agent and sub-agent control scheme in [8], where the aggregator works as master agent and each single EV is regarded as individual sub-agent. In response to the requirement from the distribution network operator, the master agent then schedules each sub-agent to achieve the objective of charging cost minimization. A penalty term that defines the cost of deviating from the average behaviour of the other sub-agents is introduced in the objective function to coordinate the sub-agents performance.

A multi-agent system based coordination of EV charging is presented in [9] and [10], where a hierarchical architecture consisting of regional aggregator agent, local aggregator agent and EV agent is proposed. These agents, together with the distribution system operator, coordinate among each other to minimise the EV charging cost using hourly data resolution. A search algorithm is employed for EV charging scheduling, the computational complexity of which increases exponentially as a function of the investigated time stamps. This would cause a potential issue for detailed simulation with relatively high time resolution.

The works mentioned above present smart EV charging approaches with different objectives, but none of them take account of the EV users' requirement in terms of battery state of charge (SoC) level, with realistic vehicle use patterns, and the network operational limits simultaneously.

A decentralised EV charging controller is proposed in [11] to optimize the charging current/power in order to meet the user's requirement, and ensure the battery's state of health is protected and voltage level is maintained at the same time. However, the proposed controller is only applied to a single EV in the studied network. The potential conflicts due to interference among multiple EV controllers, in particular those connected to the same feeder, have not been investigated. These considerations are also taken into account by [12], which aims at a flat aggregated demand profile by coordinating the response from flexible EVs and local renewable generation. A dynamic virtual pricing mechanism is adopted to achieve this target, but the price signal does not reflect realistic market arrangements.

This paper proposes a simple and effective heuristic method to minimize the EV charging cost whilst satisfying both the SoC requirement for EV battery and the normal operation of the investigated distribution network. The setting of the lower bound for battery state of charge (SoC) level has been paid special attention, in particular when there are further journeys to be made. EV use patterns have been extracted from the UK Time of Use Survey (TUS) data to with 10-minute resolution. The price signal used here is derived from the electricity system wholesale price, which provides a true representation of actual market arrangements.

Optimization model

The smart charging of EVs in this work is explored in the context of a smart grid environment where an aggregator is employed to collect information from individual EV owners and help them make decisions regarding EV charging action in response to a real time price (RTP) signal. Under such a conceptual framework it is assumed that the EV owners submit their EV usage data for the next day to the aggregator, who then schedules the EV charging profiles accordingly on a daily basis. The communication facilities between the aggregator and individual EV owners, as well as the charging interface at each of the individual households that automatically changes the charging rate according to the demand set by the aggregator, are assumed to be available as part of the smart grid infrastructure.

The objective function is expressed in Equation (1) as a charging cost minimization problem across the whole period of simulation covering all the EVs :

$$\min \left\{\sum_{i=1}^{T}\sum_{j=1}^{N}(P_i + C\eta)x_{i,j}\Delta t\right\} \quad (1)$$

Subject to:

$$\begin{cases} 0 \leq x_{i,j} \leq x^{max} & (2) \\ SoC_i^{min} \leq SoC_i \leq 100\% & (3) \\ \quad where\ SoC_i^{min} = \begin{cases} SoC_{min} & if\ there\ are\ no\ further\ journeys \\ \max(SoC_{ToD} - (ToD - i)x^{max}\Delta t\eta\ , SoC_{min}) & otherwise \end{cases} & (4) \\ SoC_\alpha + \sum_{i=\alpha}^{\beta}\left(x_{i,j}\eta\Delta t\right) = 100\%, \quad \forall j & (5) \\ V_{min} \leq \Delta V_{i,n} \leq V_{max} & (6) \end{cases}$$

where P_i is the RTP signal that varies with time i, and C represents the battery degradation cost rate in £/kWh. Parameter $x_{i,j}$ represents the EV charging rate for the j^{th} connected EV at the i^{th} time index. The charging rate is assumed in this study to be constant for each time period of duration Δt, rather than the standard process of constant current followed by constant voltage. T and N represent the total number of time steps of the simulation and number of EVs respectively.

The constraints that the objective function in Equation (1) is subject to are listed in Equations (2) to (6), where x^{max} in Equation (2) indicates the upper bound of EV charging rate. As will be presented in the next section, the charging rate with this method will take discrete values, i.e. either 0 or x^{max}, rather than a continuous range of values within the specified range. The energy required by the battery is almost always a non-integer multiple of the equivalent charging rate $x^{max}\eta$ for each charging period Δt, where η is the charging efficiency. To ensure a 100% SoC level by the end of the charging period, the last scheduled point of charge is modified to a lower charging rate.

The SoC range at each time stamp is limited as in Equation (3), where the lower bound, SoC_i^{min}, is defined in Equation (4). If no further journeys are planned, SoC_i^{min} is set to SoC_{min}. When further journeys do take place, SoC_i^{min} is determined by comparing SoC_{min} with $SoC_{ToD} - (ToD - i)x^{max}\Delta t\eta$, and taking whichever is larger. The latter term is to make sure that the required SoC level by the time of departure, SoC_{ToD}, can be achieved by charging from the i^{th} time stamp, hence ensuring the EVs' primary function for transportation. The EVs are assumed to be connected to the grid immediately after arriving at a charging place at time α, with initial battery energy SoC_{α}, until the final departure time at β. Only home place charging is considered in this work. Equation (5) assures that the battery is fully charged for each individual EVs by the end of the scheduling period. The network constraint in terms of the voltage limitation at the i^{th} time stamp for the n^{th} customer connection point (CCP) is taken into account by Equation (6).

Implementation of the optimization

Equation (1) is in the form of linear optimization, with the target of charging cost minimization driven by the time-varying equivalent charging price signal, $\mathrm{G2V_{equi}}$ as expressed in Equation (7).

$$\mathrm{G2V_{equi}} = \mathrm{P_i} + \mathrm{C}\eta \qquad (7)$$

Most of the constraints are linear apart from the voltage limitation of Equation (6), which requires power flow that is naturally nonlinear. To calculate the voltage values involved, the so-called network sensitivity matrix is employed by works such as [4, 7, 8] as mentioned in the previous section, assuming local linearity between the nodal voltage and the additional EV loads. The sensitivity matrix requires updating for every new operating point to ensure accuracy, and this makes the optimization inefficient. A dedicated network simulator, Open Distribution System Simulator (OpenDSS), is used in this work to implement the power flow for low voltage residential households. Although the optimization efficiency is not of essential importance here, OpenDSS based power flow simulation would save huge efforts compared to the sensitivity matrix updating and definitely bring more accuracy to the voltage calculations.

On top of the power flow calculation, a heuristic method is proposed to implement the smart charging target whilst satisfying the constraints regarding both battery SoC level and network. The method follows an intuitive idea of filling troughs of the price signal curve with EV charging. The process is undertaken in two steps as listed below:

1) *Schedule EV charging for each individual EV based on its availability and the price signal $G2V_{equi}$.*
   The charging energy required is due to the EV's daily driving consumption. To minimise the associated cost, the charging time slot with the lowest price value from $\mathrm{G2V_{equi}}$, as expressed in Equation (7), is selected first, provided that the EV is parked at home at this specific time stamp. It should be noted that residential charging is the only charging option used in this work, and no other charging locations are considered here. This price valley filling continues until the EV becomes fully charged. Attention is required during the scheduling process to ensure the SoC level throughout the simulation always stays within the specified range.

2) *Spot and eliminate any violated voltage points resulting from the charging profiles.*
   The total demand profiles that consist of the domestic base load (see Section 'Network layout and parameter setting' for details) and the EV charging load for individual

households are fed into the distribution network model using OpenDSS. Any detected (lower bound) voltage violations is then resolved by repetitively running the OpenDSS simulation, in each round of which any points with voltage violations are excluded from the (charging) scheduling list in order from upstream to downstream households, and the same rule as described in Step 1 is used for EV charging profile generation. The OpenDSS simulation continues until the criteria, as specified in Equation (6), is met.

Distribution network case study

Implementation of the proposed smart charging method is presented in this section using a case study of a typical domestic distribution network in the UK, in which the weekday RTP signal is used and the UK Time of Use Survey (TUS) data is used to provide the EV driving patterns and charging availability for a typical weekday. It should be noted that the RTP is an hourly based signal and the data resolution of TUS data is 10 minutes, and to deal with this difference in data resolution at each 10 minute period the price signal will be interpolated (linearly) from the hourly data available.

Real time price (RTP) signal

The online valley-filling algorithm in [2] adopts a constant pricing scheme, which is infeasible under the smart grid environment. The wholesale electricity price on the other hand is a popular choice for EV charging scheduling, either day-ahead price as in [5] or intra-day price as in [7], due to the fact that it directly reflects the supply-demand relationship in electricity market. The RTP signal is recognized to improve the performance of wholesale electricity market by mitigating market power and price volatility, [13]. A range of Real Time Pricing tariffs are presented in [13], where the wholesale electricity price is passed on to the customers together with some usage rate to recover the transmission and distribution costs. The RTP signal is derived by scaling the original wholesale electricity price to account for the proportion of this price that comprises the total customers' bill. In this work the RTP signal, P_i, is obtained by dividing the wholesale signal by 0.43 to reflect the usage rate, in line with the Ofgem statistics for 2013, [14].

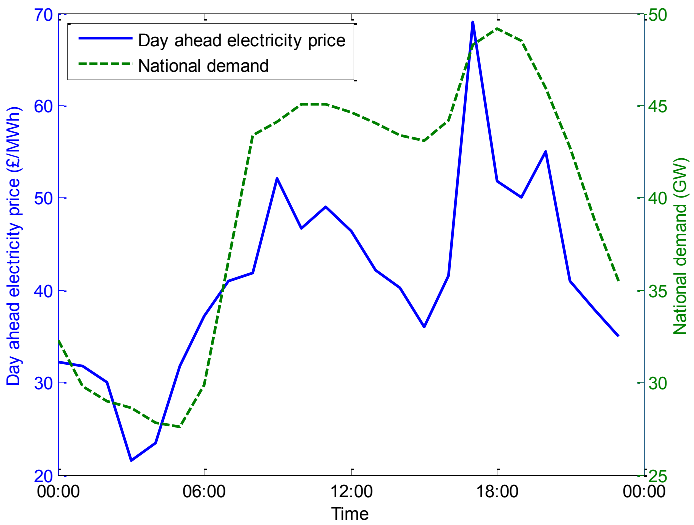


Figure 1. The UK day-ahead electricity price and associated national demand curve

The UK day-ahead electricity price for a typical January weekday from N2EX, [15], which is an electricity exchange launched in 2010, is illustrated in Figure 1 together with the corresponding national demand curve. The price signal for scheduling EV charging, $G2V_{equi}$, can then be calculated using Equation (7). The high correlation observed in Figure 1 between the price and demand curve indicates that by responding to the RTP signals the EV charging load would be scheduled to periods of low load. Cost minimization based EV charging would therefore smooth out the national demand curve.

EV usage pattern

The UK 2000 Time Use Survey records the daily activities for householders on a 10-minute basis, [16]. This data can be processed in terms of car (here assumed to be EV) using patterns to four distinct states, namely 'driving', 'parking at home', 'parking at workplace' and 'parking at other places', where other places include shopping centres, restaurants, etc. As such, the associated weekday TUS data is selected in this case. More details of the statistical characteristics of the TUS data can be found in [17].

Network layout and parameter setting

A single-phase UK distribution network with 17 households, as illustrated in Figure 2, is employed to implement the proposed algorithm for minimizing EV charging cost. The worst case scenario of 100% EV penetration is investigated here, i.e. each individual household is equipped with an EV.

Variable	**Value**
Simulation time steps	144
Total number of EV	17
Battery consumption rate due to driving	6.192kW
Battery degradation cost (C)	0.028£/kWh
Charging rate (x^{max})	3kW
Charging efficiency (η)	0.9
Minimum SoC without further journeys (SoC_{min})	20%
Minimum SoC before further journeys (SoC_{ToD})	50%
Voltage tolerance range ([V_{min}, V_{max}])	[-0.06, +0.10] p.u.

Table 1. EV assumptions and model parameter setting

The battery related assumptions and the parameter setting for the optimization function are listed in Table 1. The battery consumption rate of 6.192kW is the product of the speed assumption of 30mph, [18], and the electricity consumption figure of 12.0kWh/100km from the EV specification sheet of a BMW i3 model, [19]. According to the battery SoC constraint in Equation (5), EVs need to be fully charged by the morning departure, and the associated charging energy requirement due to driving can be calculated based on the EV driving pattern and the battery consumption rate as provided in this table. The battery degradation cost adopted here, which is 4.2 cent/kWh (2.8 pence/kWh) of throughput, is taken from the laboratory measurements based prediction in [20]. As has been mentioned in Section 'Optimization model', a fixed charging rate is specified for the EVs, rather than a continuous range of values and the charging level here uses the same value as in [21], i.e. 3kW. It should be noted that when there are no further journeys to be taken on a given day, the threshold of 20% for the minimum battery SoC value is set to prevent the battery from being over-discharged thereby causing disproportionate damage. The SoC level by departure time of further journeys has to reach as least 50% to ensure a minimal compromise of EVs' primary function as transportation. In such cases, the lower SoC bound setting before departure needs to be adjusted according to Equation (4). All charging scheduling should satisfy the voltage tolerance range of [-0.06, +0.10] p.u. at low voltage level in the UK, [22].

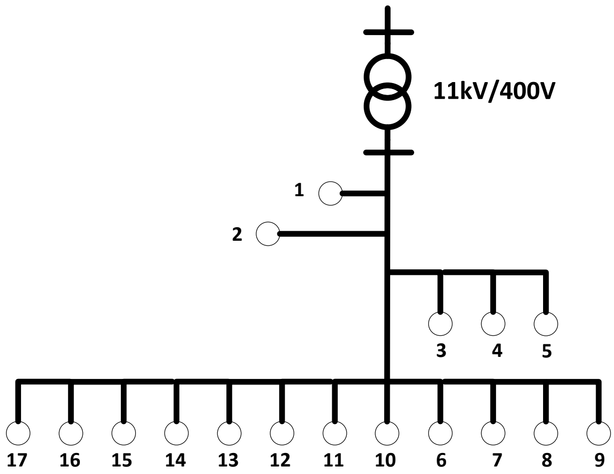


Figure 2. Single phase distribution network layout

Results and discussions

The simulated period in this study is 24 hours with a resolution of 10 minutes. The domestic base load for individual households is generated using the CREST model, [23], which is an open source tool that generates daily household electricity consumption based on a series of parameters, such as day of week, month of the year and active occupancies. A January weekday, which usually has the peak demand of the year, is chosen for this model to be consistent with the RTP signal selection, and a power factor of 0.9 is assumed for the domestic loads.

The time series of the equivalent charging price signal, $G2V_{equi}$, is illustrated in Figure 3 together with the EV state for an example household (Household 6), where the four EV states identified in Section 'EV usage pattern', 'driving' and 'parking at home' are illustrated as 1 and 2 respectively. The remaining two states, 'parking at workplace' and 'parking at other places' which are not of interest here, are shown together as 0. According to Figure 2, the vehicle at Household 6 departs from home to work at 8am and arrives back at home at 7:30pm, and then parks at home without any further journeys till next morning, which offers the flexibility of charging scheduling throughout the night when the price is low. The equivalent charging price signal shown in Figure 3 has been generated by extending the hourly signal to 10-minutes as described above, which are then used to guide charging scheduling for individual households according to the procedures outlined in Section 'Implementation of the optimization'. The associated results are illustrated in Figures 4 to 6 and household 6 is selected for illustration purposes.

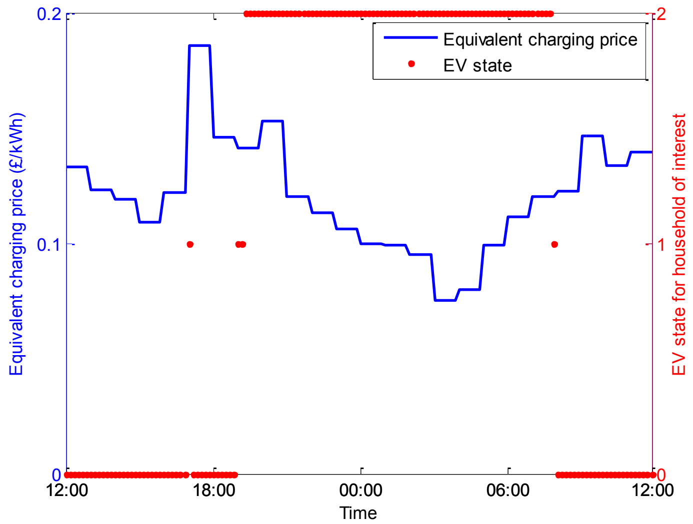


Figure 3. Illustration of the equivalent prices and EV state for Household 6

The three drops in SoC value in the battery SoC curve, as illustrated by the black dash-dot line, in Figure 4, are due to commuting consumption as indicated by the EV state in Figure 3. According to the charging rule in Section ‘Implementation of the optimization’, the first step is to schedule the charging power for the available period with lowest price until the EV is fully charged. The selected charging period for Household 6 (between 3am and 4:30am) with specified charging rate is illustrated in Figure 4 by the solid blue line, is calculated to bring the EV back to a fully charged state. The observation of lower charging rate of 0.52 kW at 4:10am is to deal with the issue of SoC overspill issue as mentioned in Section ‘Optimization model’, and this point is selected due to its having the highest price value for the scheduled charging period. The corresponding voltage level, as shown by the blue solid curve in Figure 5, however drops below the lower limit from 3:00am to 3:50am due to EV charging. Step 2 then takes into account the voltage constraints by shifting the problematic charging period to the next cheapest price period that is available. By referring to both the price signal and the EV state in Figure 3, the EV profiles gets rescheduled, as shown by dashed green line in Figure 4, with the result that the corresponding voltage profile (dashed red line in Figure 5) shows no excursion. As such, the daily EV charging cost for Household 6 is optimized to £0.38.

The optimized total EV charging cost within the simulation period of 24 hours for this investigated distribution network is £10.92. The figure before voltage constraints are taken into account is £10.82, which shows that meeting network constraints results in a small (0.9%) increase in costs.

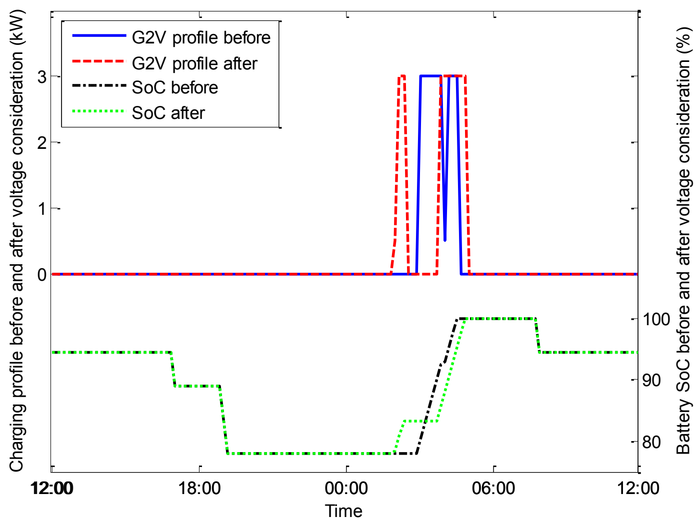


Figure 4. Smart charging results for Household 6

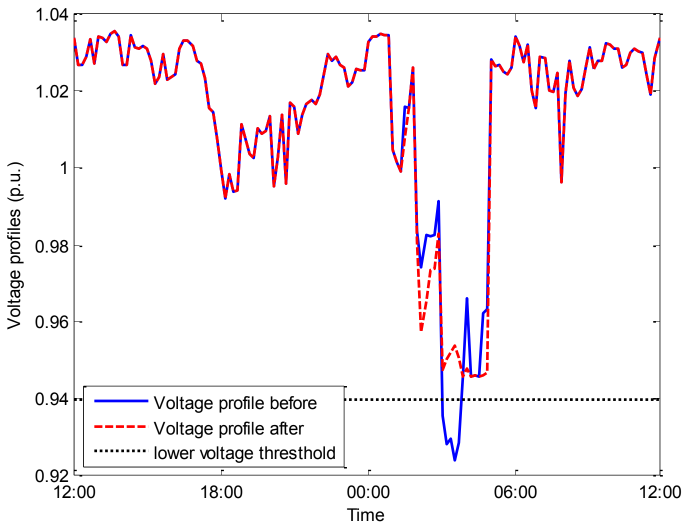


Figure 5. Voltage profile of charging scheduling for Household 6

It should be noted that the assumption of the EV being fully charged by the morning departure is made here, and the 100% SoC level is guaranteed for individual households by the end of the scheduling period according to Equation (5), which ensures the same SoC level at the start and end of the simulated cycle of 24 hours period in this case.

Figure 6 summarises the demand side response that can be provided by smart charging. By achieving the minimum cost, the total EV charging profile for the 17 households (dashed red curve) is spread across the trough of domestic base demand (solid blue curve). The EV penetration in this case is assumed to be 100%, which causes a higher recharging demand than the original domestic load peak. This is however not of concern since the associated voltage profiles are within limit, and the charging profiles would be less significant given a lower level of EV uptake. It is worth pointing out that the 100% EV penetration is only a local assumption, and the system wise EV uptake rate is assumed to be low enough to have little impact on the system price.

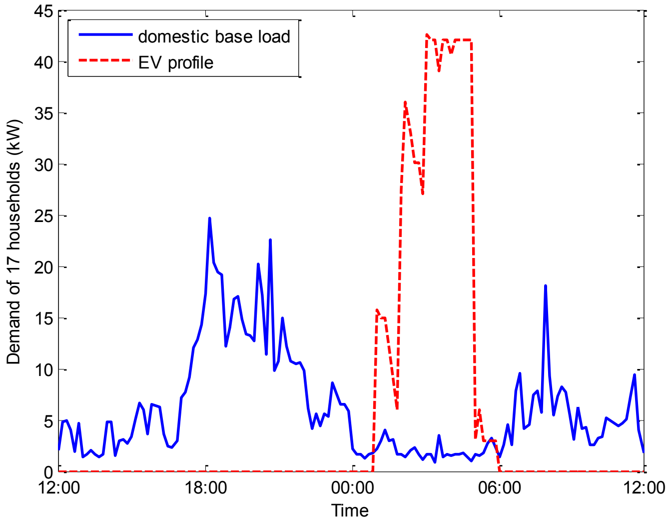


Figure 6. Aggregated demand curve for local distribution network

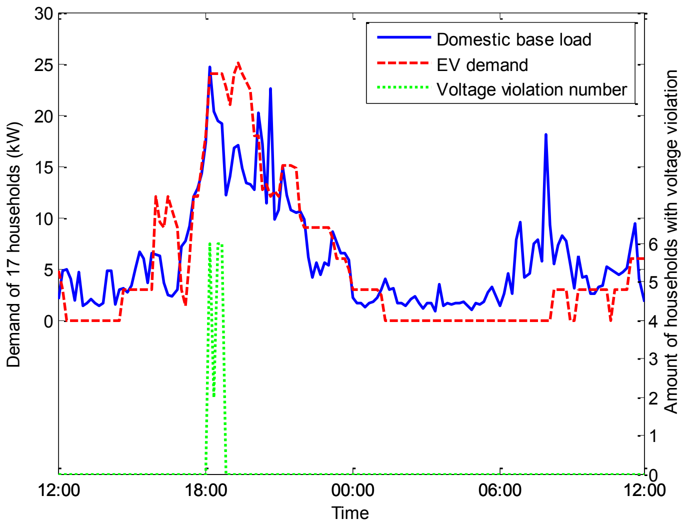


Figure 7. Uncontrolled EV charging results

Figure 7 shows the results from uncontrolled charging, where the EVs are assumed to connect to the grid and charge until full as soon as they arrive home. It can be seen that the aggregated demand due to uncontrolled charging coincides with the domestic base load and therefore causes voltage violation in more than 1/3 households in the local distribution network at around 6pm. The associated total EV charging cost for this network is £17.64, a 62% increase on the smart charging case.

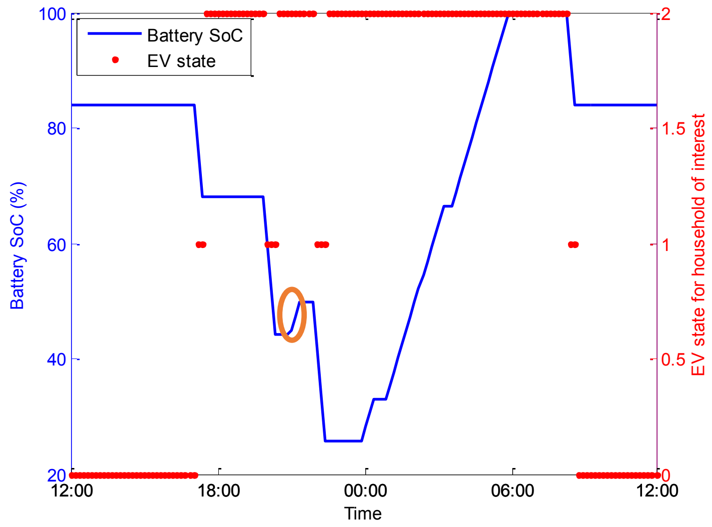


Figure 8. An example of meeting battery SoC requirement for further journeys

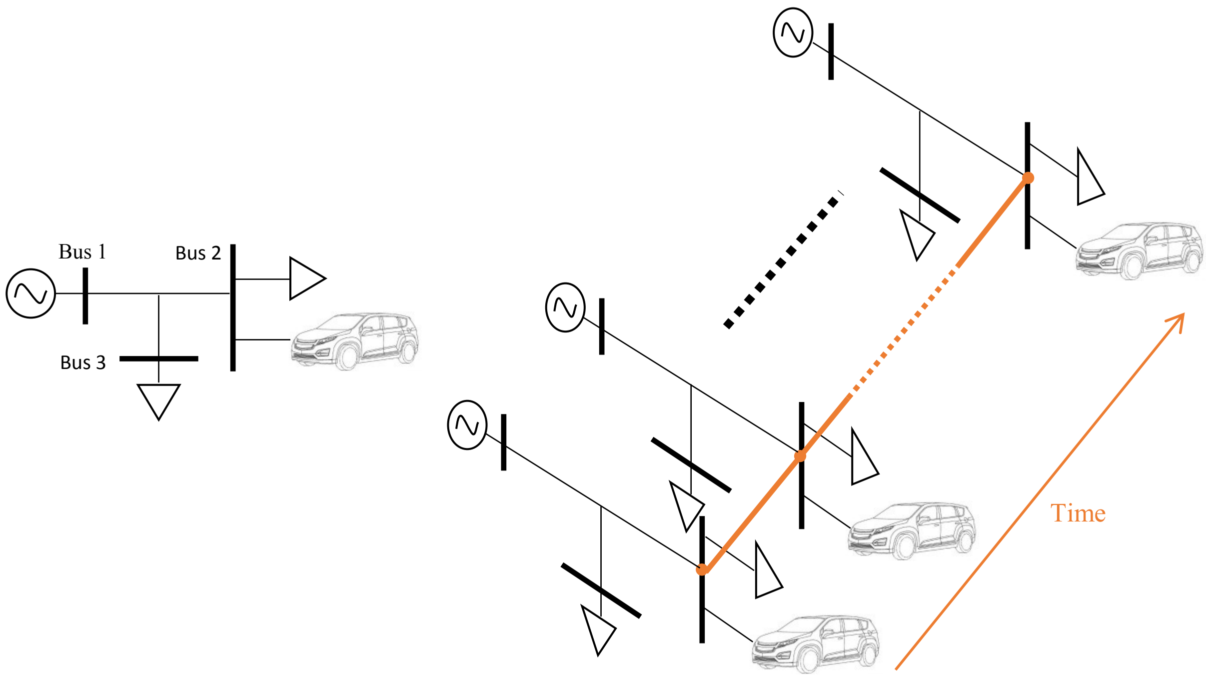
The assumptions made in this work for EV related parameters, as listed in Table 1, result in the battery SoC of all the EVs, under the current use patterns, to be at a level above 50% after the completion of trips, which automatically satisfies the requirement for further journeys. A separate case study for Household 15 is used to demonstrate the capability of the proposed method to maintain the battery SoC level as required. This is shown in Figure 8, where a higher driving consumption rate is assumed and the vehicle use pattern is illustrated together with the associated battery SoC level. It can be seen that charging is scheduled for the period between 9:30pm and 10pm (as highlighted by the orange circle in the figure) to satisfy the lower SoC bound of 50% due to the subsequent journey on that day, i.e. before 00:00. It also becomes clear by comparing the use pattern in Figure 8 with the price signal in Figure 3 that this additional charging has been undertaken using the cheapest available electricity, and thus contributes to the optimization target.

Result validation using Matpower

It should be noted that the price signal based scheduling method of charging as described in Step 1 in Section 'Implementation of the optimization' guarantees the absolute minimization of energy cost, which is however sacrificed in a minor way by considering the voltage constraints as in Step 2. The replacement of the voltage violation points by less profitable options obviously increases charging cost above the optimized value, and the associated exclusion approach, which in this case is undertaken from upstream to downstream within the network, adds uncertainty to the final optimization results. A Matpower based dynamic optimal power flow approach is presented in this section to demonstrate the effectiveness of the proposed smart charging method.

Matpower, [24], is developed as a Matlab based simulation tool dedicated for solving power flow and optimal power flow (OPF) for various network sizes and voltage levels. For a standard static OPF problem, a model including all the network elements is used to represent the power system at a single time point, where there are one reference bus, generators, transformers, transmission or/and distribution cables, fixed demands which are modelled as PQ buses, flexible demands which are modelled as generators with negative generation, or combinations of these.

The cost minimization problem here however requires a dynamic optimal power flow (DOPF) due to the fact that the objective function aims at the whole simulation time period and the associated battery SoC level for each individual EVs is linked throughout time. For instance, charging at a particular time will affect the battery SoC values for subsequent time points, each of which comes with specific SoC constraints depending on the EV status. As presented in [25, 26], the DOPF problem is modelled by replicating the static network structure and extending it along the time dimension to represent different time steps.



(a) Static OPF (b) DOPF by network extension at multiple time steps

Figure 9. DOPF concept illustration using a 3-bus system

The concept of DOPF implementation is illustrated in Figure 9 using a 3-bus system, where bus 1, bus 2, and bus 3 represent a reference bus, a flexible bus which consists of a fixed load and flexible demand from an EV, and a fixed-load bus respectively, as shown in Figure 9(a). The individual replicas of network structure in the case of DOPF, as shown in Figure 9(b), are physically independent. During the implementation of optimization, the buses connected with flexible demands (Bus 2 in each network replicas) are coupled mathematically throughout time, as illustrated by the red line, using the constraint matrix in Matpower. As such, the original DOPF problem is in effect converted to a standard OPF with a network size T times the actual one, where T is the total number of simulation time steps, and the intertemporal interaction of each flexible demand is treated as bus variable manipulation in the newly generated large-scale network at one single time step.

The optimization problem in this work is modelled by 144 (24 hours with 10 minutes simulation resolution) physically independent replicas of the network illustrated in Figure 2, each of which has its own reference bus. Since the local EV penetration is assume as 100%, each household bus in these 144 networks consists of a domestic base load, which is assumed inflexible here, and a flexible EV load, which offers the smart charging opportunity. The EV demand for the same bus at different time steps and the associated SoC constraints are taken in to account by the extended OPF.

A continuous charging rate with range 0-3kW is defined in the Matpower implementation. The ‘fmincon’ solver is chosen for this DOPF problem due to its good convergence performance for this case, and the interior point algorithm is used due to its capability of handling large-scale systems [27]. To avoid the local minima issue in the selected Matpower solver, multiple initial conditions are chosen and the ones with the best results gives a EV charging cost of £10.86 for the investigated distribution network, which is very close to the proposed heuristic solution to the smart charging case (£10.92), therefore demonstrating the effectiveness of the proposed method of EV charging cost minimization.

Conclusions

The effectiveness of the proposed heuristic method to minimize the EV charging cost has been demonstrated by comparison with results from DOPF. The SoC constraint ensures customer satisfaction, for cases both with and without further journeys after arriving at home, and the safe and acceptable operation of the network has also been guaranteed. Demand due to the smart charging has been shifted to the load trough, which avoids the network issue arising from uncontrolled charging, and the associated charging cost has been reduced significantly in relation to the uncontrolled charging case.

Future work will explore the economic feasibility of grid service provision such as frequency support from EVs where bidirectional interaction between EVs and the grid will be assumed and battery degradation cost will be properly considered.

Acknowledgements

This work was supported by the Engineering and Physical Sciences Research Council [grant number EP/K005316/1, EP/L01004/01]. The authors also wish to thank Sikai Huang for making the UK Time of Use Survey data available.

Declaration of Conflicting Interests

The Author(s) declare(s) that there is no conflict of interest.

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