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ORIGINAL RESEARCH

Efficient and robust power and energy management for large clusters of plug-in electric vehicles and distribution networks

Fotios D. Kanellos[1] | **Kostas Kalaitzakis**[1] | **Ioannis Psarras**[1] | **Yannis Katsigiannis**[2]

[1]Electrical and Computer Engineering, Technical University of Crete, Chania, Greece

[2]Electrical and Computer Engineering, Hellenic Mediterranean University, Heraklion, Greece

Correspondence

Fotios D. Kanellos, Electrical and Computer Engineering, Technical University of Crete, University Campus, Chania 73100, Greece.
Email: kanellos@ece.tuc.gr

Abstract

In this paper, an efficient and robust power and energy management for large clusters of plug-in electric vehicles (PEVs) and distribution networks is proposed. The method aims to minimise the charging cost of large clusters of PEVs in real time while ensuring distribution network normal operation and satisfying a large number of constraints from PEV level up to distribution network. The design of the method ensures very low dependence on forecast errors of critical quantities such as electricity price while it can be easily integrated with conventional optimal power flow algorithms. To this end, innovative virtual differential operation costs are assigned to clusters of PEVs. Moreover, an innovative definition of the flexibility of a cluster of PEVs to change its power is introduced while a simple idea based on the principle of the selection of the fittest is used to achieve efficient power dispatch to the PEVs with minimal computational requirements. The efficiency and the robustness of the proposed method are proved by detailed simulations of several operation scenarios of a realistic distribution network with large penetration of PEVs and renewable energy sources.

1 | INTRODUCTION

Plug-in electric vehicles (PEVs) are expected to have a key role in the reduction of greenhouse gas emissions in urban areas, energy sustainability, smart energy management and the development of the future electric power systems with large scale integration of renewable energy sources (RES) [1–3]. In this framework, a probabilistic approach for transmission expansion planning considering the uncertainty caused by the existence of PEVs is proposed in Ref. [1] while a method for optimal coordination of variable RES and PEVs to increase energy sustainability is proposed in Ref. [2]. In Ref. [3], the optimal charging of PEVs is performed taking into account the constraints of the electric power system.

Intense research has been done so far in smart power management and operation scheduling techniques for large fleets of PEVs aiming to help system operators to reduce operation cost, increase the efficiency of distribution networks, achieve large integration of RES and enhance electric power system reliability and robustness [4, 5]. In this way, the benefits from the use of PEVs are doubled as more renewable energy is produced and used to charge PEVs minimising their carbon footprint. For instance, power system restoration strategies are examined in Ref. [4] under the presence of PEVs and wind power to increase its reliability and robustness.

Most of the challenges related with power system operation under large integration of PEVs are expected in distribution networks. Low voltage operation, electrical line overloading, increased or new demand peaks over the day and higher power losses caused by non-coordinated charging of PEVs should be avoided [6, 7]. In Ref. [6], the charging of PEVs is scheduled considering demand response programs while real time control of PEVs for coordinated voltage and thermal management of LV networks is proposed in Ref. [7].

It is also noted that vehicle to grid (V2G) operation of PEVs is possible as they are usually connected to the network for enough long periods. In V2G operation, PEVs inject energy to the electric grid in order to minimise charging cost and provide demand response and ancillary services to the system such as peak-shaving or frequency support [8–11]. In this context, a new flexibility index based on the current stored energy and its respective upper and lower bounds is proposed in Ref. [8] to assess the capability of PEVs to change their power and exploited for active power regulation and provision of ancillary services for example, frequency support. A frequency regulation method for multi-area power systems with PEVs is proposed in Ref. [9] while the operation of distribution networks hosting PEVs is optimised together with the application of demand response programs in Ref. [10].

The coordinated charging of a fleet of PEVs should be beneficial for all electricity market participants. The owners of the PEVs should be provided with economic incentives, while utilities will require the mitigation of the negative impacts from the large scale integration of PEVs and network expansion minimisation [12–15]. Hence, a highly complex problem that requires the exploitation of advanced control strategies and the deployment of extended information and communication systems should be solved. In Ref. [12], PEVs connected to low voltage distribution networks are optimally controlled taking into consideration the increase of energy losses, decrease of distribution transformer lifetime, lines and transformer overload issues, voltage drops and unbalances. In Ref. [13], a decentralised charging control method is proposed for large populations of PEVs while a collaborative multi-agent system (MAS) is used in Ref. [14] in order to apply hierarchical energy management to a power distribution network with PEV integration.

MAS has been proved very efficient for such type of complex control problems [8, 14, 16]. In Ref. [16], a MAS with hierarchical structure is used to obtain optimal operation scheduling of a large port electric power system comprising a large number of refrigerated containers, PEVs, RES and ship power supplies. The agents interact until finding an equilibrium that satisfies their differentiated objectives and minimising the daily operation cost.

Several research studies have appeared in coordinated charging control of PEVs considering distribution network constraints and their impacts on them [15, 17–22]. In Ref. [18], the impact of PEVs on distribution transformers is assessed using real data while a modelling approach for PEV loads is proposed in Ref. [19]. In Ref. [20], aggregation models of PEVs are used for optimal active distribution system management while a flexible charging optimisation method considering distribution grid constraints is proposed in Ref. [21]. Power quality problems caused by PEVs are also critical for distribution networks. In Ref. [22], a single-phase on-board bidirectional charger with the capability of power conditioning is designed.

PEVs can be proved flexible prosumers as they would be able to inject power to the grid and to home (V2H operation) while their charging converters will be able to regulate the reactive power. Hence, they are expected to be major components of microgrids, smart grids and future smart homes [23–25].

The assessment of the flexibility of PEVs to participate in optimal power management programs is significant [26–29]. The research performed in Ref. [27] focusses on the flexibility assessment of commuter PEVs within a microgrid. Flexibility indicators are formed using energy capacity, power capacity, power ramp rate capacity, and energy consumption. In Ref. [28], PEV charging flexibility is characterised locally, taking into account various factors, including PEV parameters and travel needs while a game-theoretic quality of service guaranteed flexibility harvesting scheme for EVs is proposed in Ref. [29]. Several similar research efforts have considered PEV flexibility indicators. However, to the best of our knowledge there is a lack of simple analytical multi-parameter flexibility quantification indicators for PEVs and cluster of PEVs, which incorporate all the information regarding the present and projected operation state of the PEV that is necessary to optimally maintain them within the allowable operation area and reach the desired SoC level when disconnected from the network. Another interesting topic is to ensure reliable measurements and estimations needed for the optimisation of such systems. Usually, state estimation and forecasting techniques are exploited for this purpose [30].

Despite the intense research in PEV coordinated control and management, there is a gap in the development of methods exploiting simple models with guaranteed rapid convergence and increased robustness on forecast errors of major model variables for example, electricity price. The proposed method leads to cost-effective solutions that do not depend strongly on the accurate forecast of electricity price or RES production that are characterised by large errors. Moreover, the method is able to achieve several control goals and satisfy numerous constraints at all system levels without requiring the execution of complex and time-consuming algorithms. The proposed method is based on simple ideas such as the selection of the fittest and the introduction of a simple definition of the flexibility of the PEVs and clusters of PEVs to change their power. Moreover it exploits the idea of maintaining the state-of-charge of PEV battery within an area bounded by time-varying limits converging to the final target of the state-of-charge of PEV. In this way, the desired state-of-charge is reached when the PEV is disconnected from the network. A hierarchical MAS is exploited in order to deal with the increased complexity of the controlled system and collect the necessary information from several points of the network. All agent types use simple models of very low computational requirements. Some local agents perform very short-term forecasts of local loads and RES generation for example, 1-min ahead forecasting using simple ARX models [31]. The proposed method can be applied in real-time as it requires only one round of communications between the agents to find the desired operation points of the clusters of PEVs and the individual PEVs.

To the best of the authors' knowledge it is the first time that the following features are jointly applied in a coordinated PEV charging method,

- Suitable differential charging costs are assigned to the clusters of PEVs in order to consider them as dispatchable prosumers in optimal power flow (OPF) problems. The way they are defined allows the method to be economically efficient and very robust to electricity price forecast errors.
- Simple multi-parameter flexibility indicators are proposed for both PEVs and clusters of PEVs. The modelling of PEVs and charging power dispatch are simplified by using a finite operation state model and the '*selection of the fittest*' principle, respectively.
- The proposed power management method can be applied in real-time to distribution networks hosting large clusters of PEVs while the required computation time does not practically depend on the number of PEVs.

The remainder of the paper is structured as in the following. In Section 2, the structure of the proposed method and MAS, the types of agents and their functions are described. In Section 3, the models of the agents and the way they are interfaced are described. In Section 4, the efficiency and the robustness of the proposed method are proved by detailed simulations. More specifically, the proposed method is applied to the IEEE 33-bus radial distribution network with integrated PEVs and RES considering several operation scenarios. Finally, general conclusions are drawn in Section 5 and future prospects are discussed.

2 | DESCRIPTION OF THE PROPOSED METHOD AND MULTI-AGENT SYSTEM

In Figure 1, the real-world deployment of the proposed hierarchical MAS is shown while the major functions of the agents and the signals they exchange are shown in Figure 2. The detailed description of all types of agents and their models is provided in Section 3. The agents of PEV clusters collect the data sent by the PEVs for example, the power they are currently exchanging with the network, the upper and lower limits of their power and stored energy, their offers for power demand change and the respective flexibilities. The collected data are aggregated while the offers of the PEVs to change their charging power are sorted according to their flexibilities. The data collected by the PEV cluster agent together with the forecasted maximum/minimum electricity price (available by the Electric Power System Operator) and the current electricity price are used to estimate suitable differential charging costs for the cluster of PEVs. The differential charging costs reflect the current electricity price level with respect to its evolution within the receding time horizon (a time horizon of 6 h is used in this study but it can be adjusted according to application requirements). Moreover, the flexibilities of the clusters of PEVs are calculated and used together with the respective differential costs to estimate the optimal powers of the clusters. Then, the obtained optimal active powers of the clusters of

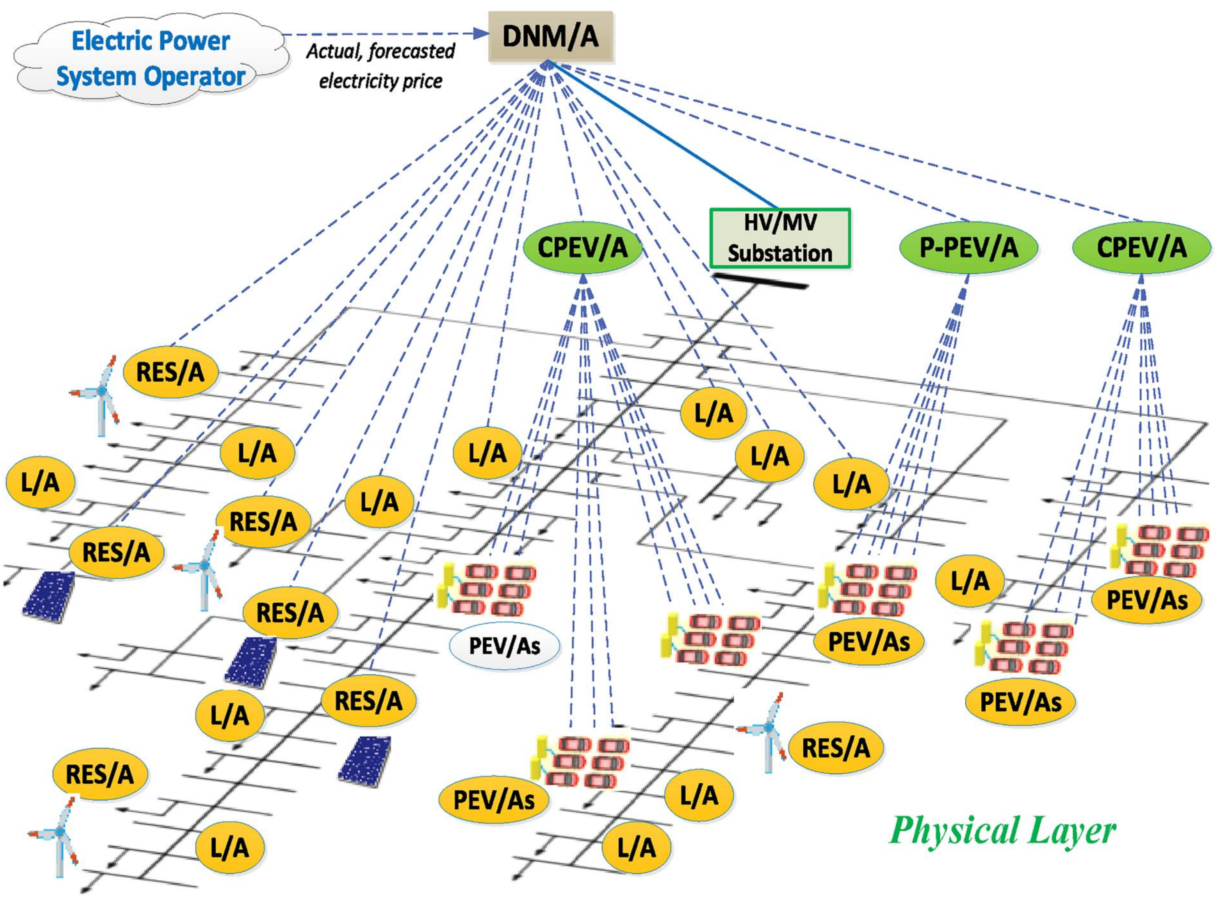


FIGURE 1 Real-world deployment of the proposed hierarchical multi-agent system

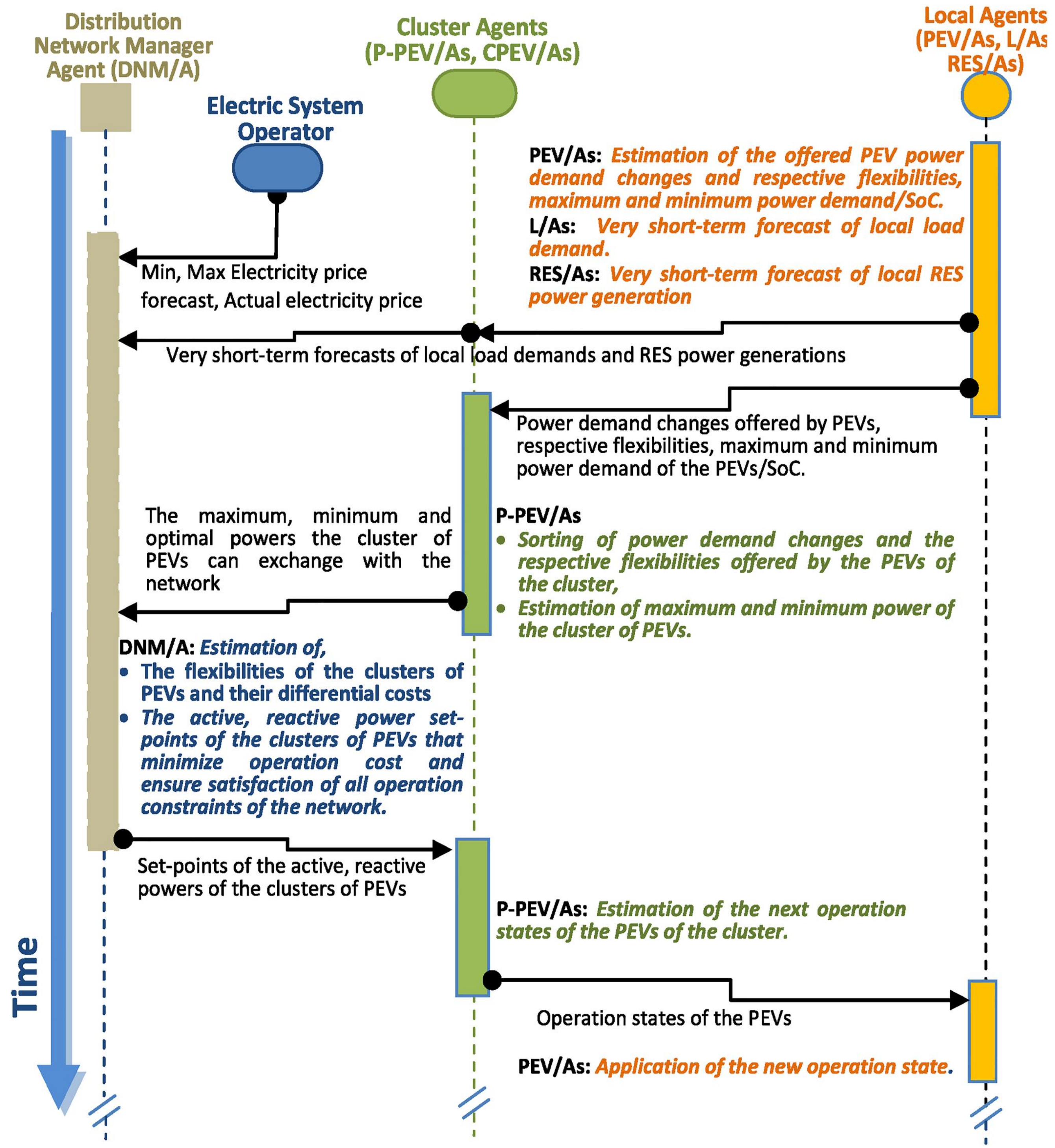


FIGURE 2 Major functions and communication signals of the proposed multi-agent system

PEVs together with short-term forecasts of RES production and local consumptions are used to solve the OPF problem of the distribution network hosting the clusters of PEVs. The obtained set-points of the active and reactive powers of the clusters of PEVs estimated by the OPF are sent back to the respective cluster agents. Finally, the active power set-points are implemented by ordering the PEVs with the higher flexibility to change their power demand. In this way, the proposed real-time control method reduces the charging cost of the hosted clusters of PEVs, maintains the voltage within the acceptable limits at all network nodes, prevents line overloading and ensures that PEV operation constraints are satisfied.

The agents used in the developed MAS can be categorised into three major types: (a) local agents that are responsible for the operation of a single component of the electric power system, (b) cluster agents that are responsible to send information to a cluster of local agents and also collect and process their responses and (c) the *Distribution Network Manager Agent* (*DNM/A*), which ensures the optimal operation of the distribution network. The operation of each agent type is briefly described in the remainder of the section. All types of agents should be equipped with a bi-directional communication system and appropriate software, while the *DNM/A* should be able to solve small scale OPF problems.

2.1 | Local agents

A local agent is assigned to each PEV, RES generator and bus load of the distribution network. Plug-in Electric Vehicle Agent (PEV/A), Renewable Energy Source Agent (*RES/A*) and bus Load Agent (*L/A*) belong to this type of agents. Local agents estimate critical quantities of the electric network components that are assigned. For instance, PEV/A estimates the flexibility of the supervised PEV to change its power demand, *RES/A* and *L/A* perform very short-term forecasts of the power generated or consumed by the components they are assigned to, respectively. Afterwards, they forward the respective information and other useful data, such as PEV identification numbers, to the cluster agent they belong and receive orders from them.

2.2 | Cluster agents

The Parking lot of PEVs Agent (P-PEVs/A) or the Cluster of PEVs Agent (*CPEV/A*) belongs to the type of cluster agents. Usually, *P-PEVs/A* or *CPEV/A* is attached to a MV/LV transformer, which exclusively supplies either a parking lot of PEVs or a cluster of spatially distributed PEVs.

P-PEVs/A or *CPEV/A* aggregates the maximum (minimum) power demand and stored energy of the PEVs it supervises. Also, it sorts PEVs' offers to change their power according to their flexibility, calculates a flexibility index for the cluster of PEVs and subsequently the optimal power demand of the cluster. Finally, it creates two lists sorted in decreasing flexibility; one for PEV active power increase and one for active power reduction, respectively. The obtained estimations are sent to *DNM/A*. Afterwards, each *P-PEVs/A* or *CPEV/A* receives by the *DNM/A* the final set-points of the total active and reactive power of the supervised cluster of PEVs. Finally, *P-PEVs/A* or *CPEV/A* determines the active and reactive power that each PEV should exchange with the network over the next time interval.

2.3 | Distribution network management agent

The distribution network management agent (DNM/A) is responsible for maintaining the active powers of all PEV clusters as close as possible to the optimal ones, estimating the optimal reactive powers of the clusters of PEVs and ensuring satisfaction of all operational and technical constraints of the distribution network. *DNM/A* receives properly processed data from all cluster agents and estimates the active and reactive power set-points for each cluster of PEVs for the next time interval by solving a suitably formulated OPF problem. The proposed MAS guarantees convergence in only one round of communications between the agents, if no communication failures exist. Agent to agent communication latencies are expected in the order of few centiles of the sec. Assuming a typical average latency of 0.15 s then according to the communication sequence shown in Figure 2b, the average duration of one round of communications will be $T = 4 \cdot 0.15$ s = 0.6 s [32].

3 | AGENT MODELLING

3.1 | Local agents

3.1.1 | PEV agent (PEV/A)

The PEVs are assumed to operate at N specific operation states as shown in Figure 3. For the sake of symmetry, N is selected to be an odd integer. The PEV can transit between neighbour states or remain at the same state. In this way unnecessary complexity resulting from a large number of possible transitions is avoided. One state is assigned to zero charging power while the rest are symmetrically assigned to G2V and V2G modes of operation.

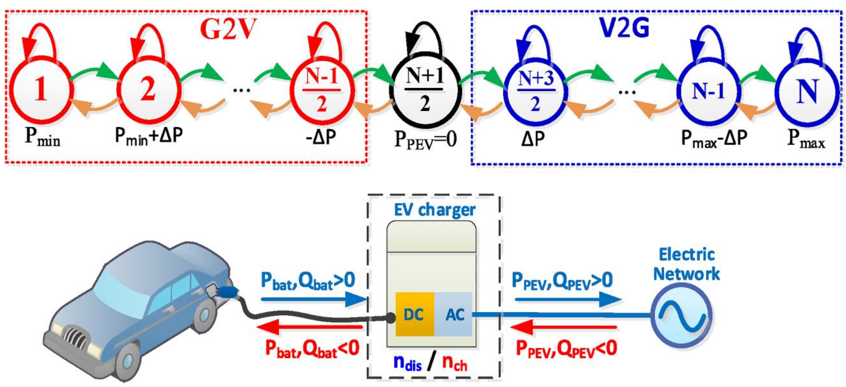


FIGURE 3 Plug-in electric vehicle (PEV) operation states (generator convention) and simplified layout of PEV electrical connection

Let us denote with S the operation state of the ith PEV and $\pm\Delta P_i$ the change of its charging power while passing from a state to its neighbour. Then, according to Figure 3, the maximum and minimum active powers ($\overline{P}_{\mathrm{PEV},i}\big|_S$, $\underline{P}_{\mathrm{PEV},i}\big|_S$, respectively), the ith PEV can exchange with the network over the next time interval provided that it is at the Sth operation state, are calculated in (1), (2).

$$\begin{aligned}\overline{P}_{\mathrm{PEV},i}\big|_{S=1\ldots N-1} &= P_{\mathrm{PEV},i}\big|_{S=1\ldots N-1} + \Delta P_i,\\ \overline{P}_{\mathrm{PEV},i}\big|_{S=N} &= P_{\mathrm{PEV},i}\big|_{S=N}\end{aligned} \tag{1}$$

$$\begin{aligned}\underline{P}_{\mathrm{PEV},i}\big|_{S=2\ldots N} &= P_{\mathrm{PEV},i}\big|_{S=2\ldots N} - \Delta P_i,\\ \underline{P}_{\mathrm{PEV},i}\big|_{S=1} &= P_{\mathrm{PEV},i}\big|_{S=1}\end{aligned} \tag{2}$$

with

$$\Delta P_i = \frac{P_{\mathrm{PEV},i}\big|_{S=N} - P_{\mathrm{PEV},i}\big|_{S=1}}{N}$$

where, $P_{\mathrm{PEV},i}\big|_S$ is the active power the ith PEV exchanges with the electric network when it is at the Sth operation state.

It should be taken into consideration that the reactive power of the ith PEV should not result to apparent power bigger than the nominal. This constraint is formulated in (3).

$$\left|\, Q_{\mathrm{PEV},i} \,\right| \le \sqrt{\overline{S}_{\mathrm{PEV},i}^{\;2} - P_{\mathrm{PEV},i}\big|_S^{\,2}} \tag{3}$$

Assuming generator convention, then the energy stored in the battery of the ith PEV at the end of the next time interval, $\widehat{E}_{\mathrm{PEV},i}(t+\Delta t)$, is estimated according to (4).

$$\widehat{\mathrm{E}}_{\mathrm{PEV},i}(t+\Delta t) = \begin{cases} \mathrm{E}_{\mathrm{PEV},i}(t) - P_{\mathrm{PEV},i}(t+\Delta t)\cdot n_{\mathrm{ch}}\cdot \Delta t, & P_{\mathrm{PEV},i}(t+\Delta t) < 0 \\ \mathrm{E}_{\mathrm{PEV},i}(t) - \dfrac{P_{\mathrm{PEV},i}(t+\Delta t)}{n_{\mathrm{dis}}}\cdot \Delta t, & P_{\mathrm{PEV},i}(t+\Delta t) \ge 0 \end{cases} \tag{4}$$

where, $\mathrm{E}_{\mathrm{PEV},i}(t)$ is the energy stored in the battery pack of the ith PEV at time t and $n_{ch(\mathrm{dis})}$ is the charging (discharging) efficiency factor of PEV charging system. In this study, it is assumed that $n_{ch} = n_{\mathrm{dis}} = 0.93$.

The area on the stored energy-time plane the PEV is allowed to operate is shown in Figure 4. It is bounded by dynamic upper ($E_{\mathrm{PEV\_high}}$) and lower ($E_{\mathrm{PEV\_low}}$) bounds converging to the target of the stored energy ($E_{\mathrm{PEV,t}}$) at the scheduled disconnection time t_f. Each boundary consists of four line segments. For instance, the upper boundary of the PEV stored energy comprises:

- The segment (O–A1) which begins from the point O corresponding to the energy stored in PEV battery when it is plugged to the network and extends to point A1 where the maximum stored energy $\overline{E}_{\mathrm{PEV}}$ is reached given that it is charged using its maximum charging power.
- The segment (A1–B1) where the PEV has the maximum allowed energy stored in its battery.
- The segment (B1–C1) where the PEV discharges with the maximum allowed discharging power until it slightly exceeds the target of the stored energy ($(1 + a)\cdot E_{\mathrm{PEV,t}}$). The parameter α is defined by the user and it is usually a small number in the range [0.01 0.025].
- The segment (C1–D1) which exists only if the EV driver changes the initial schedule and decides to unplug the PEV

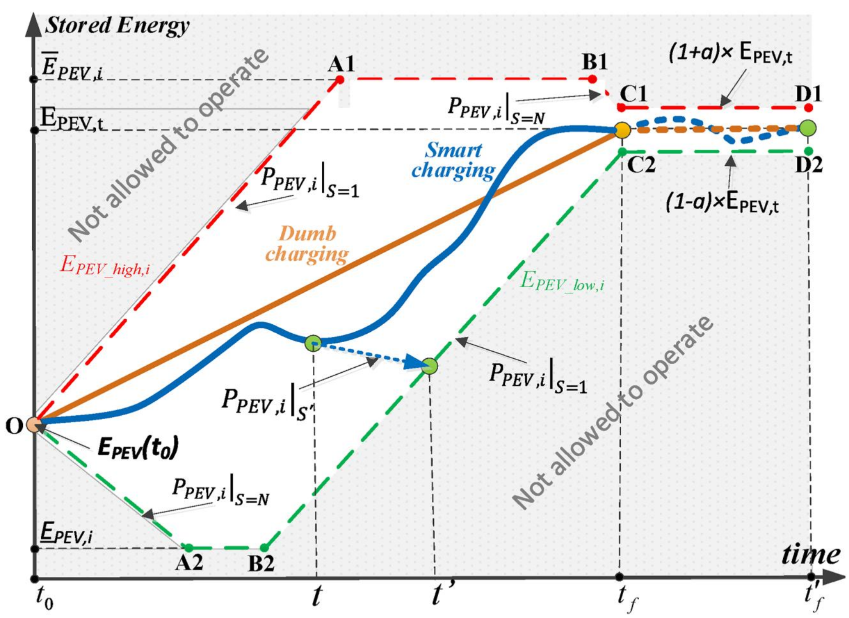


FIGURE 4 Dynamic upper/lower bounds of plug-in electric vehicle stored energy and 'Smart' and 'Dump' charging trajectories

at time t'_f after the initially scheduled time t_f. In this case, the maximum allowed stored energy remains constant and equal to $(1 + \alpha) \times E_{\mathrm{PEV,t}}$.

The respective segments (O–A2), (A2–B2), (B2–C2) and (C2–D2) constitute the lower bound of the stored energy.

The flexibility of the ith PEV to transit to the Sth state over the next time interval is estimated in (5). According to this approach, the flexibility of a PEV to absorb or inject power is reduced when $E_{\mathrm{PEV,\ high}}$ or $E_{\mathrm{PEV,low}}$ curve is approached, respectively. The proposed flexibility index is taking into account the major characteristics of PEVs' batteries and therefore ensures fair estimation of the flexibility for different types of PEVs.

$$\mathrm{flex}_i(t) = t_i'(t) - t = \begin{cases} \dfrac{E_{\mathrm{PEV,i}}(t) - E_{\mathrm{PEV\_high,i}}(t_i')}{P_{\mathrm{PEV},i}\big|_{S'}}, & P_{\mathrm{PEV},i}\big|_{S'} < 0 \\ \dfrac{E_{\mathrm{PEV,i}}(t) - E_{\mathrm{PEV\_low,i}}(t_i')}{P_{\mathrm{PEV},i}\big|_{S'}}, & P_{\mathrm{PEV},i}\big|_{S'} > 0 \end{cases} \quad (5)$$

Each PEV sends the data calculated above to the supervising cluster agent (*P-PEVs/A* or *CPEV/A*), where they are aggregated, and the operation of the cluster of PEVs is optimised in real time.

3.1.2 | RES agent (RES/A) and load agent (L/A)

The main tasks of *RES/A* and *L/A* are to perform very short-term forecasts of the RES generator power production and load power consumption, respectively. In this study, one-minute ahead forecasting is adopted. Classical autoregressive models have been proved very efficient for such type of applications while they can be implemented very easily [31].

The models implemented for RES/A and L/A are given in (6)–(9).

$$\widehat{P}_{\mathrm{RES}/A}(t+\Delta t) = \sum_{i=0}^{p} a_i \cdot P_{\mathrm{RES}/A}(t - i\cdot\Delta t) \ + e_{\mathrm{RES}/A}(t) \quad (6)$$

$$\widehat{Q}_{\mathrm{RES}/A}(t+\Delta t) = \frac{\sqrt{1 - PF^2_{\mathrm{RES}/A}}}{PF_{\mathrm{RES}/A}} \widehat{P}_{\mathrm{RES}/A}(t+\Delta t) \quad (7)$$

$$\widehat{P}_{L/A}(t+\Delta t) = \sum_{i=0}^{q} b_i \cdot P_{L/A}(t - i\cdot\Delta t) \ + eP_{L/A}(t) \quad (8)$$

$$\widehat{Q}_{L/A}(t+\Delta t) = \sum_{i=0}^{r} c_i \cdot Q_{L/A}(t - i\cdot\Delta t) \ + eQ_{L/A}(t) \quad (9)$$

where, $\widehat{P}_{\mathrm{RES}/A}$ and $\widehat{Q}_{\mathrm{RES}/A}$ are the very short-term forecasts of the active and reactive power produced by the RES supervised by the RES/A, $PF_{\mathrm{RES}/A}$ is the power factor of the RES, $\widehat{P}_{L/A}$ and $\widehat{Q}_{L/A}$ are the very short-term forecasts of the active and reactive power of the load supervised by the L/A, a_i, b_i, and c_i are the parameters of the autoregressive models and $e_{\mathrm{RES}/A}$, $eP_{L/A}$, and $eQ_{L/A}$ are the respective model errors.

The above models can be continuously trained using updated datasets allowing model parameters to be adjusted in real time and ensure high forecast accuracy [31, 33].

3.2 | PEVs parking lot (or cluster of PEVs) agent-(P-PEVs/A)

P-PEVs/A collects their offers from the supervised PEV/As to change their power demands over the next time interval and the respective flexibilities to apply them. *P-PEVs/A* sorts them in the descending order of flexibility and the data are registered into two matrices SL_+ and SL_-, which correspond to the positive and negative power demand changes offered by the PEVs, respectively. Each matrix contains three columns: (1) The PEV power demand (injection) offer for the next time interval, (2) PEV flexibility, and (3) PEV identification number. After the sorting process, the elements of matrices SL_+ and SL_- satisfy the following equations and conditions.

$$SL_{+(-)}(j,1) = P_{\mathrm{PEV},i+(-)}(t+\Delta t),$$
$$SL_{+(-)}(j,2) = \mathrm{flex}_{i,+(-)}(t), \quad SL_{+(-)}(j,3) = i \quad (10)$$

with,

$$SL_{+(-)}(j,2) \geq SL_{+(-)}(j+1,2) \quad \forall j,\ 1 \leq j \leq N_{\mathrm{PEV}} - 1$$

where, i denotes the ith PEV of the cluster and j the jth row of $SL_{+(-)}$, N_{PEV} is the number of the PEVs of the cluster, and $flex_{+(-)}$ (i,t) denotes the flexibility of the ith PEV at time t to increase (decrease) its active power to $P_{\mathrm{PEV}+(-)}(i, t+\Delta t)$ at time $t + \Delta t$.

Furthermore, *P-PEVs/A* determines the fittest set of PEVs that should change their operation state in order to ensure accurate tracking of the active power set-point of the cluster of PEVs received by the *DNM/A*. The problem is reduced to locate the mth row of $SL_{+(-)}$, such as if the PEVs registered at the rows above it change operation state then the active power set-point of the cluster is accurately followed. This procedure is synopsised into the pseudocode tabulated in Table 1. P^s_{cl}, used in Table 1, is the active power set-point for the cluster of PEVs that is estimated by the *DNM/A* and will be described in paragraph 3.3.3.

Let us assume that $\mathfrak{J}$ is t he optimal subset of the PEVs within the cluster that should change their operation state. The ith PEV belongs to $\mathfrak{J}$ if the following conditions are valid.

$$i = SL_{+(-)}(j,3) \ \in \ \mathfrak{J} \quad \forall\ j \leq m \quad (11)$$

TABLE 1 Pseudocode for the determination of the PEVs that should change state of operation

$\ddot{P}_{cl}(1) = SL_{+(-)}(1,1);$

$\ddot{P}_{cl}(2) = SL_{+(-)}(1,1) + SL_{+(-)}(2,1);\ m = 2;$

While $\left(P_{cl}^{s} - \ddot{P}_{cl}(m)\right) \cdot \left(P_{cl}^{s} - \ddot{P}_{cl}(m-1)\right) > 0$

Do

$\ddot{P}_{cl}(m+1) = \ddot{P}_{cl}(k) + SL_{+(-)}(m+1,1);$

$m = m + 1;$

End

The total reactive power the cluster of PEVs exchanges with the network is proportionally dispatched to each PEV of the cluster according to (12).

$$Q_{\mathrm{PEV},i}(t+\Delta t) = \underline{Q}_{\mathrm{PEV},i}(t+\Delta t) + p \cdot \left(\overline{Q}_{\mathrm{PEV},i}(t+\Delta t) - \underline{Q}_{\mathrm{PEV},i}(t+\Delta t)\right) \tag{12}$$

with,

$$p = \frac{Q_{\mathrm{cl}}^{s}(t+\Delta t) - \sum_i \underline{Q}_{\mathrm{PEV}}(i, t+\Delta t)}{\sum_i \overline{Q}_{\mathrm{PEV}}(i, t+\Delta t) - \sum_i \underline{Q}_{\mathrm{PEV}}(i, t+\Delta t)}$$

where, Q_{cl}^{s} is the set-point of the reactive power of the cluster received by *DNM/A*, $Q_{\mathrm{PEV},i}$ is the estimated reactive power of the *ith* PEV, and $\overline{Q}_{\mathrm{PEV},i}$ and $\underline{Q}_{\mathrm{PEV},i}$ are the maximum and the minimum reactive powers of the *ith* PEV, respectively.

The minimum and maximum values of the energy stored by the cluster of PEVs are calculated according to (13)–(14).

$$\underline{E}_{\mathrm{cl}}(t) = \sum_i \underline{E}_{\mathrm{PEV},i}(t), \quad \overline{E}_{\mathrm{cl}}(t) = \sum_i \overline{E}_{\mathrm{PEV},i}(t) \tag{13}$$

$$\underline{P}_{\mathrm{cl}}(t) = \sum_i \underline{P}_{\mathrm{PEV},i}(t), \ \overline{P}_{\mathrm{cl}}(t) = \sum_i \overline{P}_{\mathrm{PEV},i}(t) \tag{14}$$

Finally, the *P-PEVs/A* sends the calculated values of $\underline{E}_{cl}$, $\overline{E}_{cl}$, $\underline{P}_{cl}$ and $\overline{P}_{cl}$ to the *DNM/A*.

3.3 | Distribution network manager agent (DNM/A)

DNM/A is responsible for the calculation of the set-points of the active and reactive powers absorbed or injected by the clusters of PEVs. These set-points are derived according to the maximum and minimum forecasted electricity price over the receding time horizon and satisfy all distribution network constraints. In order to achieve the above, the *DNM/A* solves an OPF problem [34], where the clusters of PEVs are considered as prosumer entities and handled as virtual generators, which are able to produce and consume active and reactive power. In order to set-up the OPF problem, the following assumptions were done:

- A virtual operation cost, $C_{cl,k}(t)$, is assigned to the kth cluster of PEVs at time t. It is approximated by a second order polynomial function of the active power, $P_{cl,k}(t)$, the kth cluster exchanges with the network at time t. Therefore the respective differential charging costs will be linearly proportional to the active powers of the clusters. This approach is consistent with the classical set-up of OPF problems.
- Slack bus is handled as a virtual generator with its differential charging cost being equal to the actual electricity price $\Pi(t)$.
- The forecasted maximum and minimum electricity prices, $\widehat{\overline{\Pi}}$ and $\widehat{\underline{\Pi}}$, within the receding time horizon (the next 6 h are used in this study) are considered known.
- The maximum (minimum) power of each cluster of PEVs is matched with the forecasted maximum (minimum) value of the electricity price over the receding period, $\widehat{\overline{\Pi}}$ and $\widehat{\underline{\Pi}}$, respectively. Next, the optimal active power of the cluster of PEVs corresponding to the actual electricity is estimated. It is noted that the upper and lower limits of the active powers of the clusters of PEVs and the electricity price vary with time.
- Very short-term forecasts of the power productions by the RES generators connected to the network are estimated by the respective local agents for example, 1 min ahead forecast.
- Likewise the case of RES generators, very short-term forecasts of the active/reactive power demands of the MV network bus loads are estimated by the respective local agents.

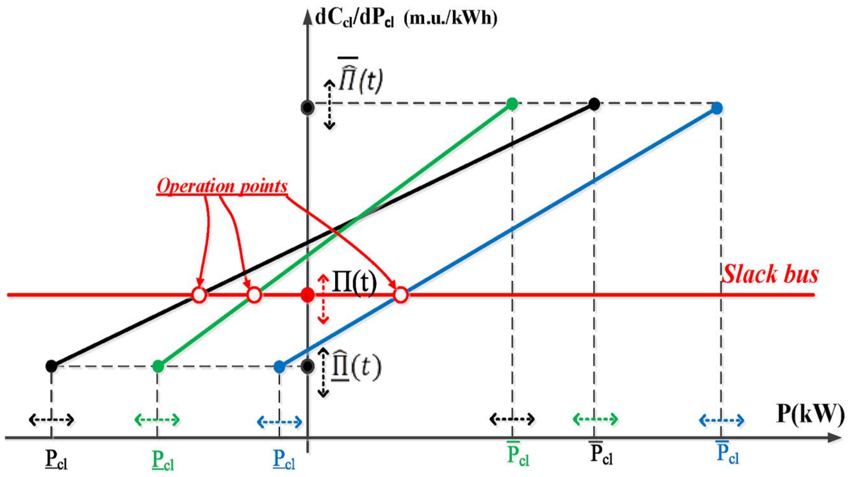
3.3.1 | Estimation of PEV cluster virtual differential charging cost

According to economic power dispatch problem [34, 35], the variable operation cost of a power production system is minimised when the differential charging costs of all power generation units become equal. Therefore, the operation points of the clusters of PEVs are the intersections of their differential costs and the differential cost of the slack bus (electric power system). Indicative differential charging costs of three PEV clusters and the slack bus are shown in Figure 5 (generator convention is used).

Let us consider that the differential charging cost of the kth cluster of PEVs is given by the following equation

$$\frac{dC_{cl,k}\left(P_{cl,k}(t)\right)}{dP_{cl,k}} = \alpha_k(t) \cdot P_{cl,k}(t) + b_k(t) \tag{15}$$

FIGURE 5 Graphic representation of indicative differential charging costs of plug-in electric vehicle (PEV) clusters (generator convention).



Moreover, the kth cluster of PEVs is required to produce maximum (minimum) power when the forecasted electricity price is maximum (minimum). Hence,

$$\overline{\overline{\Pi}}(t) = \alpha_k(t)\cdot \overline{P}_{cl,k}(t) + b_k(t) \tag{16}$$

$$\underline{\widehat{\Pi}}(t) = \alpha_k(t)\cdot \underline{P}_{cl,k}(t) + b_k(t) \tag{17}$$

with,

$$\overline{\overline{\Pi}}(t) = \max\left\{\Pi(t), \max\left\{\widehat{\Pi}(t)\right\}\right\}, \quad t \in \left[t,\ t+T_f\right]$$

$$\underline{\widehat{\Pi}}\ (t) = \min\left\{\Pi(t), \min\left\{\widehat{\Pi}(t)\right\}\right\}, \quad t \in \left[t,\ t+T_f\right]$$

where, T_f denotes the receding time horizon, where maximum and minimum values of the electricity price are forecasted. It is easily derived from (16), (17) that

$$\alpha_k(t) = \frac{\overline{\overline{\Pi}}(t)(t) - \underline{\widehat{\Pi}}(t)}{\overline{P}_{cl,k}(t) - \underline{P}_{cl,k}(t)}, \qquad b_k(t) = \underline{\widehat{\Pi}}\ (t) - \alpha_k(t)\cdot \underline{P}_{cl,k}(t) \tag{18}$$

According to the previous analysis, the optimal power that should be exchanged by the kth cluster of PEVs and the network is calculated by (19).

$$P^*_{cl,k}(t) = \frac{\Pi(t) - b_K(t)}{\alpha_k(t)} \tag{19}$$

3.3.2 | Estimation of PEV cluster active power set-point

The DNM/A calculates the energy stored by the kth cluster of PEVs at the end of the next time interval as in the following.

$$\widehat{E}_{cl,k}(t+\Delta t) = \begin{cases} E_{cl,k}(t) - P^*_{cl,k}(t\ )\cdot n_{ch}\cdot \Delta t, & P^*_{cl,k}(t\ ) < 0 \\ E_{cl,k}(t) - \dfrac{P^*_{cl,k}(t\ )}{n_{dis}}\cdot \Delta t, & P^*_{cl,k}(t\ ) \geq 0 \end{cases} \tag{20}$$

The flexibility of a cluster of PEVs to change its active power is calculated in a similar way with the flexibility of a single PEV. In (21), the energy stored by the cluster of PEVs, the maximum/minimum stored energy and the maximum/minimum power the cluster of PEVs can exchange with the electric network are exploited to calculate the flexibility of the cluster of PEVs.

$$\text{flex}_{cl,k}(t) = t_k{}' - t \tag{21}$$

with $t_k^{'}$ satisfying the following conditions,

$$0 \leq \overline{E}_{cl,k}(t_k{}') - E_{cl,k}(t) + \sum_{t:\Delta t:t_k{}'} \underline{P}_{cl,k}(t)\cdot \Delta t < \varepsilon,$$

$$\text{for } P^*_{cl,k}(t) < 0$$

$$0 \leq \mathrm{E}_{\mathrm{cl},k}(t) - \sum_{t:\Delta t:t_k{}'} \overline{P}_{cl,k}(\mathrm{t})\cdot \Delta t - \underline{\mathrm{E}}_{\mathrm{cl},k}(t_k{}') < \varepsilon,$$

$$\text{for } \mathrm{P}^*_{\mathrm{cl,k}}(\mathrm{t}) \geq 0$$

where, ε is a small positive number.

Finally, in addition to the optimal active power estimated in (19), the flexibility of the kth cluster of PEVs is taken into account in order to derive its active power set-point, $P_{cl,k}^{'}$, as shown in (22).

$$P'_{cl,k}(t) = \begin{cases} P^*_{cl,k}(t), & \text{flex}_{cl,k}(t) \geq A \\ F \cdot P^*_{cl,k}(t) - (1-F) \cdot \overline{P}'_{cl,k}(t), & \\ \text{flex}_{cl,k}(t) < A \text{ and } P^*_{cl,k}(t) < 0 & \\ F \cdot P^*_{cl,k}(t) - (1-F) \cdot \underline{P}'_{cl,k}(t), & \\ \text{flex}_{cl,k}(t) < A \text{ and } P^*_{cl,k}(t) \geq 0 & \end{cases} \tag{22}$$

with,

$$F = \frac{\text{flex}_{cl,k}(t)}{A}, \quad \overline{P}'_{cl,k}(t) = -\frac{d\overline{E}_{cl,k}(t)}{dt},$$
$$\underline{P}'_{cl,k}(t) = -\frac{d\underline{E}_{cl,k}(t)}{dt}.$$

The parameter A denotes the flexibility threshold, which is decided by the operator of the system. In this work, it was considered that A equals to the 10% of the maximum value of the flexibility of the kth cluster at time t that is, $A = 0.1 \cdot \overline{\text{flex}}_{cl,k}(t)$. Equation (22) ensures that when the flexibility of the cluster of PEVs becomes smaller than a specific threshold A, then its active power set-point is suitably adjusted in a way that the upper and lower bounds of the energy stored by the cluster of PEVs are never violated.

3.3.3 | Distribution network optimal power flow

Another task of DNM/A is to solve the OPF problem that ensures the satisfaction of all distribution network operation constraints while maintaining the active powers of the clusters of PEVs that are very close to their set-points as they were calculated in (22). The OPF problem was solved using MatPower [34]. MatPower uses a sum of polynomial functions of the generator active powers as the objective function. Hence, the objective function given in (23), which uses second order polynomials of the active powers of the clusters of PEVs and ensures convergence to their set-points, was used in this study. It is noted that the used OPF algorithm is also able to regulate the reactive powers of the clusters of PEVs in order to support the voltage at their connection points.

$$J = \min_{P^s_{cl,1} \cdots P^s_{cl,k}} \left\{ \sum_k \left({P^s_{cl,k}}^2 - 2P'_{cl,k} \cdot P^s_{cl,k} + {P'_{cl,k}}^2 \right) \right\} \tag{23}$$

The objective function is subject to the satisfaction several constraints. More specifically, voltage amplitude, branch currents, PEV clusters' active and reactive powers are maintained within their limits. The aforementioned constraints are suitably defined in MatPower software.

The major points of the developed method are briefly summarised in the following. The information is exchanged by MAS agents in a bottom-up and up-bottom direction to implement the power set-points in one round of communications. Local agents are responsible to implement the power set-points assigned to them by the cluster agents. The objective of PEV cluster agents is to apply the set-points received by the DNM/A (which solves the respective OPF problem) by selecting the PEVs having the bigger flexibility. The objectives of PEV agents are to implement the set-points assigned to them by the respective PEV cluster agents, maintain the energy stored in their batteries within the allowable limits and ensure that the SoC target is reached when they disconnect from the network. The above objectives are ensured by appropriate dynamical upper and lower limits applied to PEV SoC and the way PEV flexibility is defined. It is noted that the active power set-points of PEV clusters are estimated in a way to ensure reduction of their charging cost.

4 | CASE STUDY

The IEEE 33-node radial distribution feeder was appropriately modified for the purposes of this study. The examined distribution network is shown in Figure 6. The nominal voltage of the network is 20 kV and three parking lots (PLs) comprising 250, 100, and 90 charging points are connected to it. In this case study, five operation states have been considered for each PEV that is, $N = 5$ in (1) and (2).

The PLs are connected to nodes 14, 27 and 31. Also, the examined network comprises three photovoltaic systems (PVs) connected to the nodes 7, 19 and 29, and one group of small wind turbines (WTs) connected to node 18. In this study, PVs and WTs are assumed to operate with unit power factor, while the loads of the distribution network operate with inductive power factor equal to 0.9.

24 h time series of the total active power consumed by the distribution network loads and total active power generation of the PVs and WTs were produced for the simulation of the examined system. Three hundred different trajectories were randomly produced for each of the aforementioned quantities to address their stochastic nature. The trajectories used next for demonstration purposes and the respective variation areas are shown in Figure 7. Similarly, 300 different trajectories of the actual electricity price were randomly produced. The trajectory of the actual electricity price used next for demonstration purposes, the electricity price forecast with the respective error and the variation area of the electricity price are shown in Figure 8. The electricity price is considered to change every 15 min. The abbreviation m.u. denotes the monetary unit.

The examined 24 h period was divided into 1 min time intervals. Hence, the DNM/A receives data from the local agents and calculates the new set-points for the clusters of PEVs every 1 min.

Four types of PEVs with V2G capability are considered in this study. Their major technical characteristics are tabulated in Table 2.

The PLs of the examined distribution network are assumed to host PEVs whose drivers are doing different types of

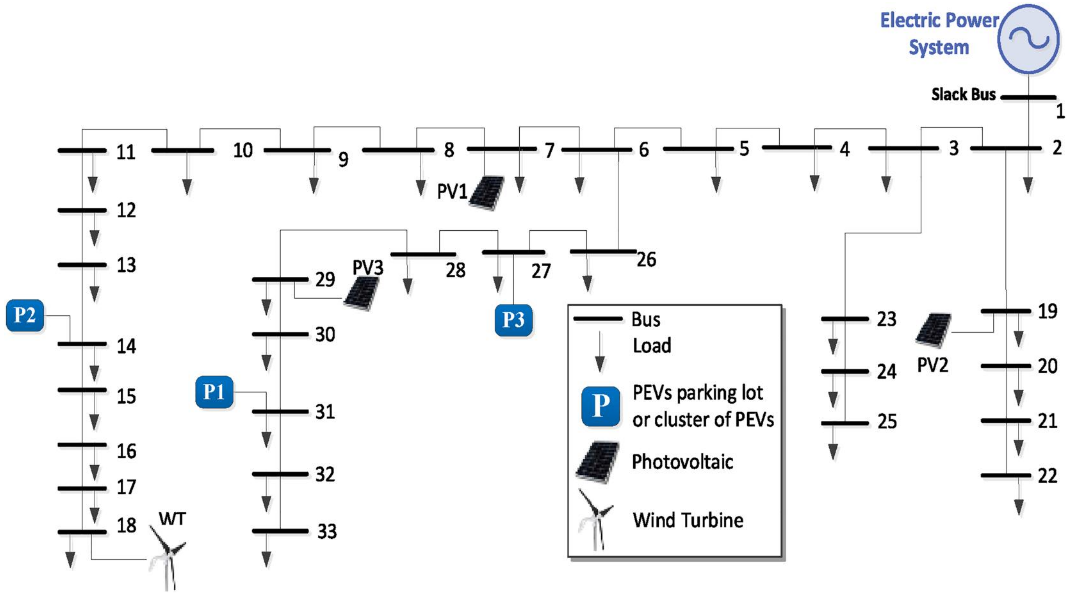


FIGURE 6 Single-line diagram of the examined electric distribution network

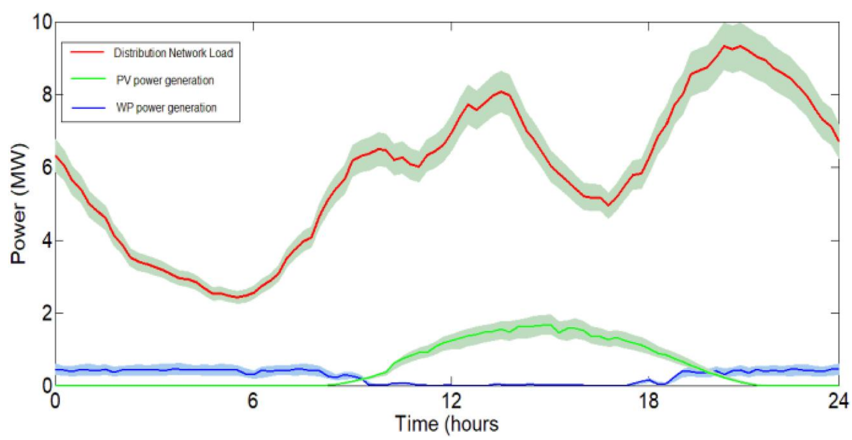


FIGURE 7 Distribution network total active power consumption, renewable energy sources power generation (photovoltaic system, wind) and their variation areas

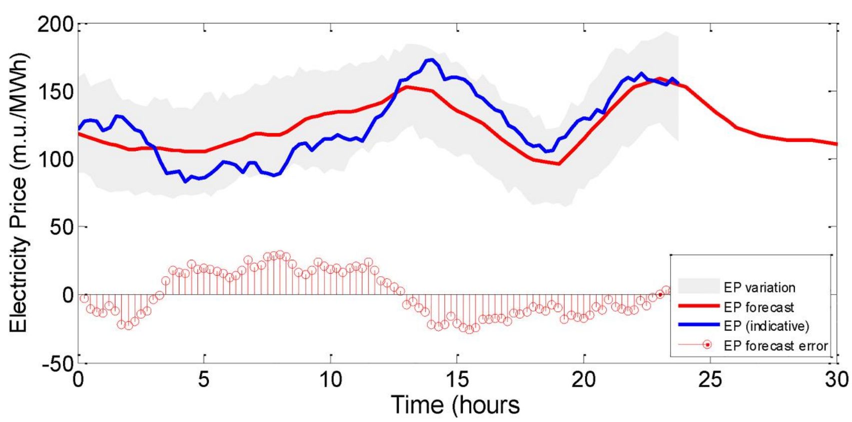


FIGURE 8 Actual electricity price with its variation area and electricity price forecast

activities. More specifically, the chargers of the first PL (PL1) supply PEVs whose drivers are at home, the chargers of the second one (PL2) supply PEVs of citizens being at work and the half chargers of the third one (PL3) supply PEVs of citizens being at work while the remaining chargers supply PEVs of citizens doing social activities. The probability density functions used in this paper for the dwell and arrival times of the PEVs for each type of activity were extracted using the database provided in Ref. [36] and they are shown in Figure 9. In this way, the stochastic behaviour of the EV drivers was simulated for all examined cases of system operation.

Three operation scenarios, as tabulated in Table 3, are considered in the following analysis. In *SC*1, the proposed smart charging method is applied. It requires only short-term forecasts of the minimum and maximum values of the electricity price. In *SC*2, classical multi-period charging optimisation is applied at PL level with its major target being the minimisation of PEVs' charging cost. It requires an accurate electricity price forecast and it is sensitive to the respective forecast errors. Moreover, it does not support distribution network voltage support and it does not consider distribution network constraints.

TABLE 2 Plug-in electric vehicle parameters

	PEV type			
	1	**2**	**3**	**4**
$\overline{E}_{\mathrm{PEV}}$ /$\underline{E}_{\mathrm{PEV}}$ (kWh)	15/3	19/3	25/4	30/5
$\overline{P}_{\mathrm{PEV}}$ /$\underline{P}_{\mathrm{PEV}}$ (kW)	10/−10	12/−12	16/−16	20/−20
$\overline{S}_{\mathrm{PEV}}$ (kVA)	10	12	16	20

Abbreviation: PEV, plug-in electric vehicle.

The optimisation problem solved in *SC*2 for each PL or cluster of PEVs is given in (24)–(29).

$$C = \min_{P_{cl}} \left\{ \sum_{n=1}^{96} P_{cl}(n \cdot \Delta t) \cdot \widehat{\Pi}(n \cdot \Delta t) \right\} \tag{24}$$

subject to,

$$P_{cl}(n \cdot \Delta t) \geq \underline{P}_{cl}(n \cdot \Delta t) \quad \forall\, n \tag{25}$$

TABLE 3 Distribution network operation scenarios

	Operation scenario		
	SC1	**SC2**	**SC3**
Proposed smart charging method	√	-	-
Electricity price forecast	-	√	-
Max/min electricity price forecast	√		
Dumb charging	-	-	√
Classical charging optimisation	-	√	-
Voltage support	√	-	-
Network constraints	√	-	-

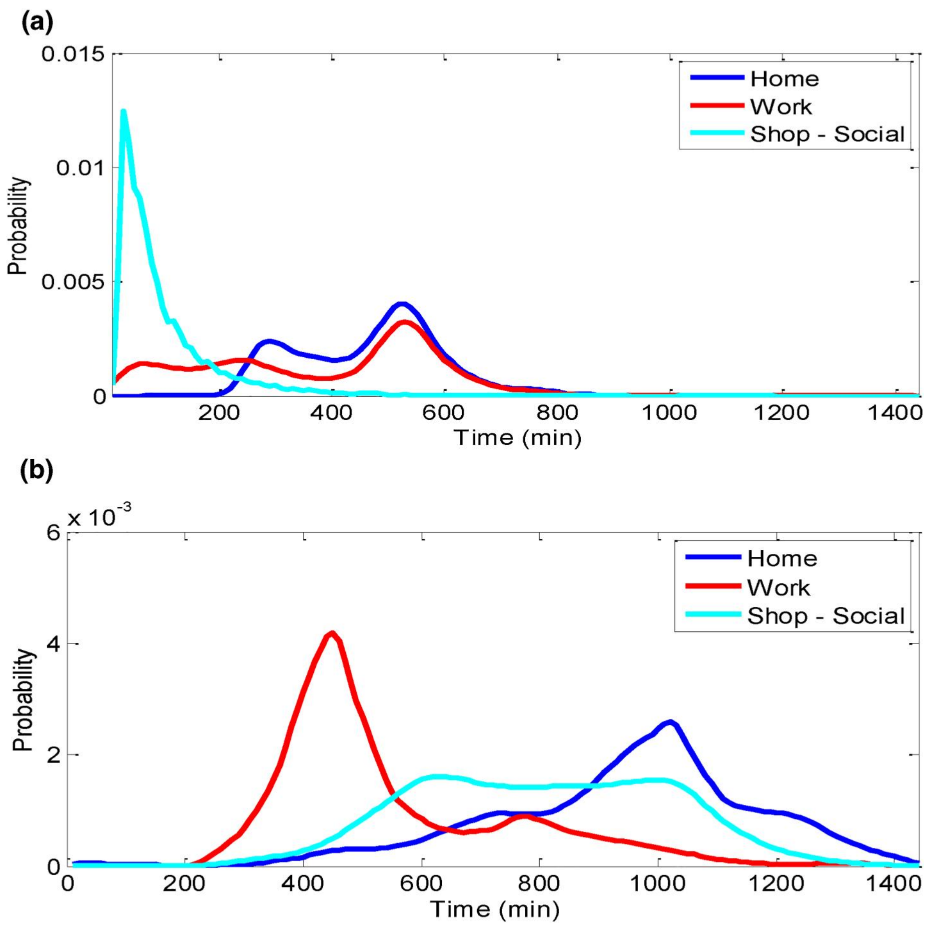


FIGURE 9 (a) PDF of plug-in electric vehicles' dwell time and (b) PDF of PEVs' arrival time

$$P_{cl}(n\cdot\Delta t)\le \overline{P}_{cl}(n\cdot\Delta t)\ \ \forall\, n \tag{26}$$

$$E_{\mathrm{cl}}(\mathrm{n}\cdot\Delta t)\ge \underline{E}_{cl}(n\cdot\Delta t)\ \ \forall\, n \tag{27}$$

$$E_{cl}(n\cdot\Delta t)\le \overline{E}_{cl}(n\cdot\Delta t)\ \ \forall\, n \tag{28}$$

$$E_{cl}(T)=E_{cl,t} \tag{29}$$

$E_{cl,t}$ is the desired stored energy of the cluster of PEVs at the end of the optimisation period. For a fair comparison of the examined scenarios, $E_{cl,t}$ was set equal to the energy stored by the PLs at $t = T$ in $SC1$.

In $SC3$, '*dumb*' charging is applied to the PEVs of all PLs. In this scenario, all PEVs draw the constant amounts of power required to reach their targets of stored energy when they are disconnected from the network. Electricity price variations, network loading network voltage limits etc. are not considered in $SC3$.

Three hundred operation cases were simulated for the operation scenarios $SC1$, $SC2$, and $SC3$ using the randomly reproduced load, RES production and electricity price time series in order to assess the robustness and effectiveness of the proposed method. The indicative results presented next correspond to the respective trajectories shown in Figures 7 and 8.

The active powers the PLs exchange with the network are shown in Figure 10 for each operation scenario. In $SC1$ and $SC2$, PLs absorb large amounts of active power during low electricity price periods in order to minimise their charging cost. In some cases, they also inject power to the electric network when the electricity price is high. The same conclusions can be drawn by the trajectories of the stored energy of the PLs depicted in Figure 11 for SC1 and $SC2$. The qualitative characteristics of the trajectories are similar for both scenarios. However, there are differences as the optimal charging scheduling method proposed in this article approaches the problem in a very different way than the conventional multi-period charging optimisation method.

The flexibility of the PLs and the flexibility of the EVs connected to a charging point of PL1 together with the respective stored energy and its limits are shown in Figure 12a,b for $SC1$. It can be seen from these figures that the flexibilities of the PLs and the PEVs vary according to the distance of the current SoC from the respective technical limit.

In $SC1$, the PEVs regulate their reactive powers in order to maintain the voltage at the electric distribution network busses within the acceptable limits. In $SC2$ and $SC3$, the PEVs operate with unity power factor. All bus voltages of the examined distribution network obtained in $SC1$ are shown in Figure 13. In this study, upper and lower voltage limits were set to 1.1 p.u. and 0.9 p.u., respectively. It is verified by the simulation results that all bus voltages are maintained between upper and lower voltage limits in $SC1$. It is also verified by the obtained results that all PEVs manage to reach their SoC targets in SC1.

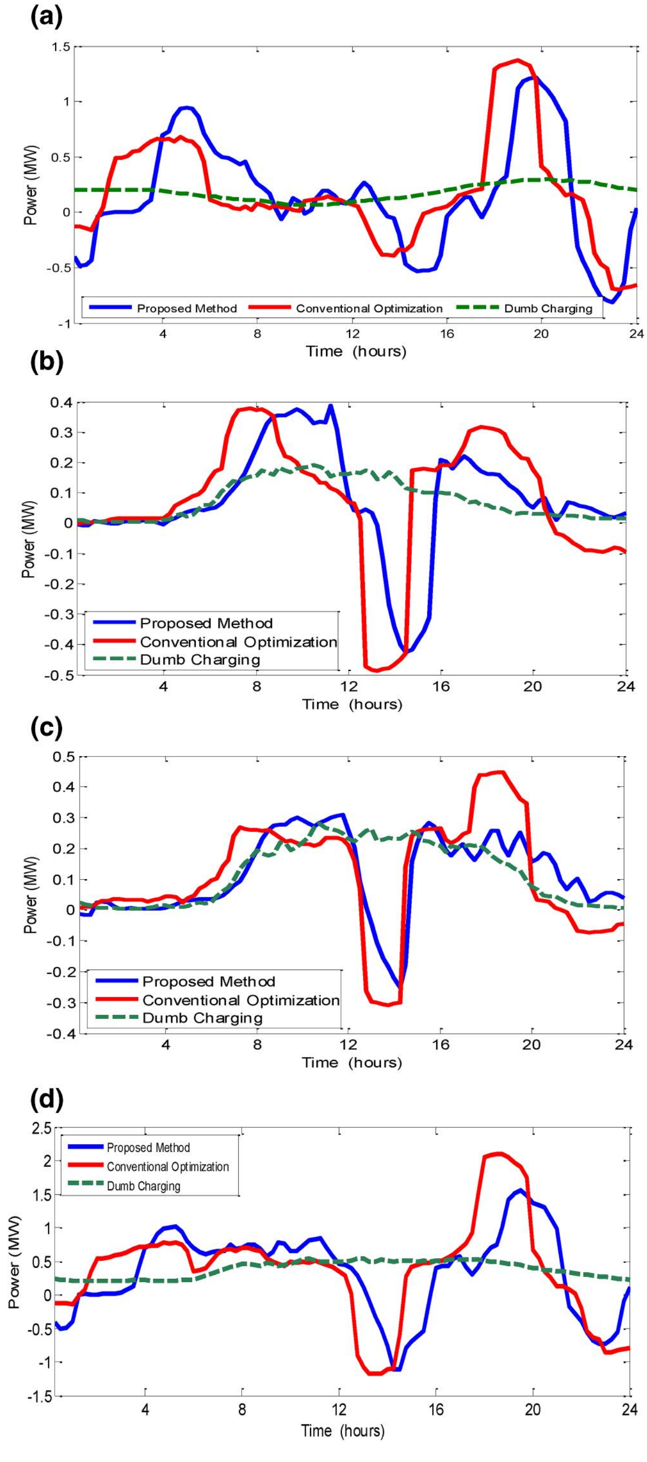


FIGURE 10 (a), (b), (c) Active power exchanged by the PLs 1, 2 and 3 and the network (load convention) and(d) Total active power exchanged by all parking lots (PLs) and the network (load convention)

The average total charging cost of the 300 operation cases under the operation scenarios $SC1$–$SC3$ amounted to 746, 814 and 1012 m.u./day, respectively. The proposed method ($SC1$) leads to an average 26.28% charging cost reduction with regard to the '*dumb*' charging scenario ($SC3$) while the classical charging optimisation method ($SC2$) leads to a respective

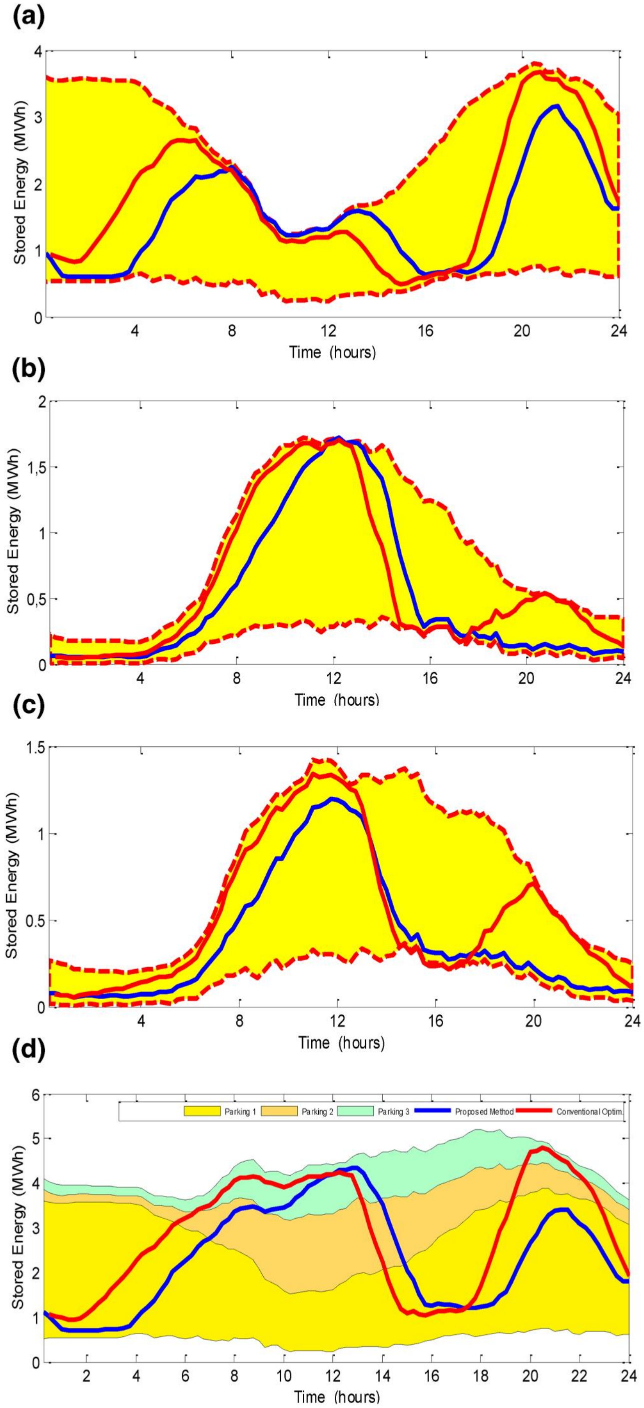


FIGURE 11 (a), (b), (c) Energy stored by the parking lots (PLs) 1, 2 and 3 (the blue line corresponds to the proposed method and the red line to conventional optimisation method) and the respective upper/lower bounds (dashed red lines) and (d) Total energy stored by all PLs and its upper/lower bounds in stack form

charging cost reduction of 19.57%. It can be concluded from the obtained results that the proposed method leads to a significant charging cost reduction, ensures satisfaction of all applied constraints for all examined operation cases and hence, it is more robust to forecast errors.

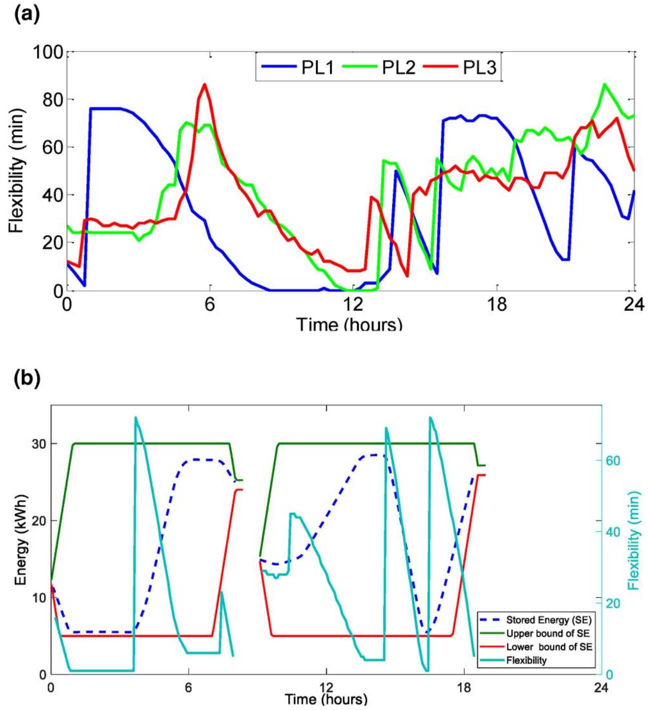


FIGURE 12 (a) Parking lots' flexibilities and (b) upper and lower limits of plug-in electric vehicles connected to a charging point of PL1 and the respective flexibilities

It should be noted that a bigger number of PEV operation states was also used to test the performance of the method. More specifically, nine PEV operation states were considered instead of five. The obtained results were almost identical to those obtained by the five state PEV model, leading to the safe conclusion that a bigger number of PEV operation states is not necessary as it only increases the complexity of the model without affecting the efficiency of the method.

The average calculation time per round of communications required by the agents was 0.86 s. Assuming a typical average latency of 0.15 s for communications, then according to the communication sequence shown in Figure 2b the average duration of one round of communications will be $T = 4{\cdot}0.15$ s $+$ 0.86 s $=$ 1.46 s, which is much more smaller than the used 1-min time intervals used for the real-time application of the method [32].

5 | CONCLUSION

An innovative method for efficient and robust power and energy management of large clusters of PEVs and distribution networks is proposed in this paper. The major innovative points of the method are the introduction of virtual operation costs for clusters of PEVs, the simple definition of the flexibility of PEVs and cluster of PEVs to change their power and the exploitation of the selection of the fittest principle in order to achieve an effective power dispatch to the PEVs in real time according to their flexibility. Moreover, the way the virtual

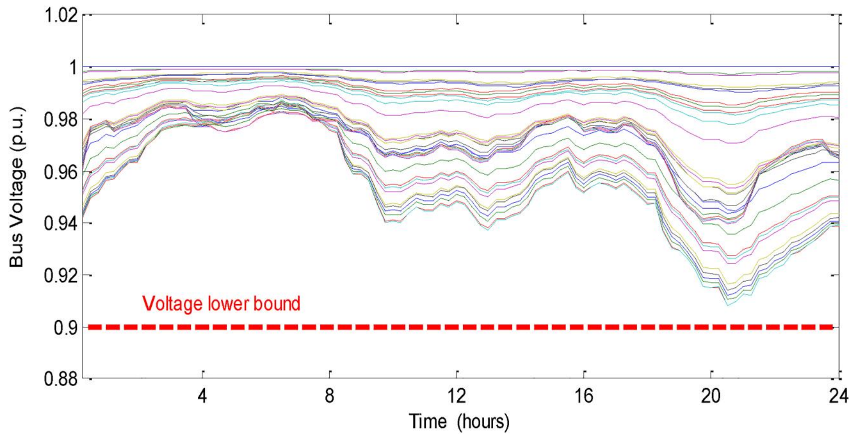


FIGURE 13 Bus voltages (p.u.) obtained in SC1

operation cost of a cluster of PEVs is defined ensures the robustness of the method to electricity price forecast errors. The above are jointly exploited to formulate a conventional OPF problem and apply it to real world distribution networks with high penetration of PEVs. The application of the method requires the deployment of a hierarchical MAS comprising three levels of hierarchy and several types of agents. The proposed method is based on the exploitation of models with low computation requirements while the way it is designed ensures low execution time regardless PEV population. It was proven that the average duration of one round of communications between the agents including the required computation time is approximately 1.5 s, which is much smaller than the typical requirements for real time applications in distribution networks. The proposed method was tested using a large set of different operation cases and it was shown that it leads to a significant charging cost reduction with regard to conventional multi-period optimisation methods.

Some technical challenges in real world applications will probably arise from the inaccurate or partial knowledge of distribution network model parameters and the unavailability of some of the required network measurements. In this regard, the exploitation of parameter and state estimation techniques could constitute possible future work. Other possible future expansions of this work could be as follows:

- An effort to define PEV and cluster of PEVs' flexibilities in a way that PEV battery early ageing from successive charging/discharging cycles will be limited.
- The development of an algorithm for the fair dispatch of the economic profits of PEV aggregators to the PEVs they control.
- The exploitation of the method by PEV aggregators for optimal ancillary services to the network for example, frequency support.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Authors elect to not share data.

ORCID

Fotios D. Kanellos https://orcid.org/0000-0003-0433-1395

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