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A multi-agent based scheduling algorithm for adaptive electric vehicles charging

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HIGHLIGHTS

- A decentralised EV charging control model was developed.
- EV were separated in "Responsive" and "Unresponsive" EV to control signals.
- Generation and demand forecasts were considered in the charging control model.
- The adaptive behaviour of Responsive EV agents was experimentally demonstrated.

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ABSTRACT

This paper presents a decentralized scheduling algorithm for electric vehicles charging. The charging control model follows the architecture of a Multi-Agent System (MAS). The MAS consists of an Electric Vehicle (EV)/Distributed Generation (DG) aggregator agent and "Responsive" or "Unresponsive" EV agents. The EV/DG aggregator agent is responsible to maximize the aggregator's profit by designing the appropriate virtual pricing policy according to accurate power demand and generation forecasts. "Responsive" EV agents are the ones that respond rationally to the virtual pricing signals, whereas "Unresponsive" EV agents define their charging schedule regardless the virtual cost. The performance of the control model is experimentally demonstrated through different case studies at the micro-grid laboratory of the National Technical University of Athens (NTUA) using Real Time Digital Simulator. The results highlighted the adaptive behaviour of "Responsive" EV agents and proved their ability to charge preferentially from renewable energy sources.

1. Introduction

The integration of electric vehicles is considered as a promising alternative to reduce transportation related emissions and improve energy consumption efficiency. Recent studies [1–3] reveal that a fuel-driven vehicle can produce less greenhouse gas emissions (GHG) than an EV if the recharging energy is entirely produced by coal-fired power plants. Therefore, charging EV from renewable energy (e.g. solar, wind) significantly contributes to achieve real environmental benefits.

However, it is difficult to effectively utilise this intermittent and dispersed generation capability due to its direct dependency on local weather factors. High penetration levels of renewable energy resources and other low carbon generation technologies are affecting the generation mixture of each country. At those high uptakes, the distributed generators will cause voltage rises during times of low demand at the low voltage (LV) feeders [4–12].

In addition, changes in the electricity demand will occur as a result of EV uptake. Due to the temporal and spatial variability of EV charging energy patterns, the load demand at the national level is expected to increase. According to [13–20] the impacts of EV charging in distribution network will create higher power peaks, overload power transformers, cause voltage drops and line overloading.

Demand side management is seen as an effective solution to address these challenges in the existing distribution networks. Electric vehicles offer opportunities for effective demand side management, utilising their flexibility with regards to the time of charging. Therefore, EV charging management is a potential candidate solution to shift charging demand based on the renewable energy production or to shift charging to off peak hours, decreasing voltage fluctuation and transformer loading.

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Due to the EV impacts on distribution networks, EV charging control models have attracted substantial research attention [21]. In literature, there are two main types of EV charging control models: the centralized and the decentralized. In a centralised control strategy, a central control unit is responsible to manage the EV charging demand, controlling directly the charging process of each EV. Such examples of control strategies can be found in [22–44]. Although this control strategy offers a simple way to manage the EV charging requests, it is not appropriate for large numbers of EVs as it requires high computational power and an advanced communicational infrastructure to avoid delays and enable real time operation. Concerns have also been expressed regarding the data privacy of the EV drivers, as their charging habits and information would be collected in one place, increasing the risk of being exposed to malicious cyber-attacks.

Decentralised control approaches, where the intelligence is distributed among the components of the system, are seen as a potential solution to overcome these problems. Papers [45–51] present decentralized control models for coordinating the EV charging. In these papers, the decision making processes are mainly done by the EVs which only require knowledge of the local condition of the system. Therefore, the complexity of such control approaches is usually low and the computational and communicational cost is reduced compared to the centralised approaches. Decentralised price-based EV charging control strategies have also been investigated in [52–56] for the control of Distributed Energy Sources (DER)/DG, assuming that an appropriate pricing scheme could trigger certain responses from the participants. Paper [55] presents a market clearing model which does not require any centralized knowledge of participants' properties. The model is extended in [52], however its feasibility is not ensured with respect to nodal power balance constraints when the participant's coordination problem is not strictly convex. In order to address this issue, the authors of [56] are using the primal average technique on all the past iterations in order to show an asymptotic convergence to a feasible and optimal solution. However, this approach is not always feasible due to the huge computational and communicational costs it creates. The infeasibility problems of [52] are solved in [54], where the price responses of non-strictly convex DERs are considered fixed. However this approach creates significant new demand peaks, as the price responses are concentrated at the lowest-priced periods of the coordination horizon. To overcome this problem, a non-linear pricing scheme is adopted in [53]. In these control approaches, the synchronisation of the participants is critical. The existing approaches require simultaneous exchange of information among all participants which might lead to response delays or even lost information. To the best of the authors' knowledge this problem is not addressed in the literature when considering a decentralised EV charging management scheme.

All the above references suffer from the assumption that every available DG/DER is controllable and responds logically to a pricing scheme, without considering uncertainties related to the EV driver preferences. EV charging coordination is highly affected by the EV driver behaviour, as the driver decides when and how to charge its vehicle. Dealing with the uncertainties related to the EV charging patterns is important for all charging control models. In [23,27,28,31], forecasting actions are included in the presented centralised charging control models. Statistical models and Markov-processes are used to deal with the uncertainties related to the EV travel patterns [23] and renewable generation output [31]. In the majority of these papers, it is mentioned that the performance of the control model is depended on the accuracy of the predictions. According to the best of the authors' knowledge, there are no decentralised charging control models utilising forecasting procedures to deal with the uncertainties regarding EV participation in the control scheme.

In this paper a decentralized scheduling algorithm for EV charging is presented. The charging control model follows the architecture of a Multi-Agent System (MAS). Each entity was modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. The MAS consists of an EV/DG aggregator agent and "Responsive" or "Unresponsive" EV agents. The EV/DG aggregator agent is responsible to maximize his profit by designing the appropriate virtual pricing policy according to accurate power demand and generation forecasts. Responsive EV agents are the ones that respond rationally to the virtual pricing signals, whereas Unresponsive EV agents define their charging schedule regardless the virtual cost. Responsive EV agents are adjusting their charging schedules according to the charging demand from "Unresponsive EV agents", indicating their adaptive behaviour. A novel algorithm was developed for the distributed management of EV charging. Although the EV agents are selfishly trying to minimize their virtual cost, this results in a valley-filling effect on the total demand curve. This is achieved through the dynamic pricing mechanism of an EV/DG aggregator. The virtual pricing scheme is used only for the coordination purposes of the EV/DG aggregator and does not reflect the actual network charges or market prices. It is assumed that all EV owners that participated in the charging management scheme will be benefited from a lower electricity rate. The actual charging cost of each EV owner is post calculated but this is out of the scope of this paper.

The main technical contributions of this paper are as follows:

(i) The proposed control model considers a realistic scenario for the future EV fleet by classifying the EV agents into Responsive and Unresponsive to the control strategy.
(ii) A forecasting model is integrated to the decentralised charging control model in order to reduce the uncertainties associated with the participation of EVs to the management scheme.
(iii) The synchronisation of the EV charging coordination is achieved by a novel approach involving sequential updates of the charging control signals. By modifying the virtual control price signals after each charging request sequentially, the Responsive EV agents adapt their charging demand to the demand from the Unresponsive EV agents.
(iv) The performance of the control model was experimentally demonstrated at the Electric Energy Systems Laboratory hosted at the National Technical University of Athens (NTUA). Three factors were investigated: (a) the location of the EV/DG aggregator, (b) the importance of forecasting the demand from Unresponsive EV agents and (c) the charging behaviour of Responsive EV agents when renewables generation is available. The results showed the adaptive behaviour of Responsive EV agents and proved their ability to charge preferentially from Renewables.

The rest of the paper is organized as follows. In Section 2 the EV Management Framework is illustrated. The experimental demonstration of the charging control model is described in Section 3. Conclusions are drawn in Section 4.

2. EV management framework

2.1. Architecture

The EV management scheme follows a two-layer decentralized structure based on the UK generic distribution network [57]. The bottom layer includes the EV agents at the LV customer level, whereas the top layer includes the EV/DG aggregator agents at the MV/LV transformer level.

The EV/DG aggregator agent represents an energy market entity which manages the EV charging demand and owns small scale renewable energy generation in a geographical area. It tries to maximize its profit from existing contractual agreements with the EV owners and the distribution network operator. The EV/DG aggregator purchases energy from the wholesale energy market, based on forecasts for the next day's local EV charging demand and local renewable energy generation. The EV charging requests are operated in order to maximize the use of the local renewable energy and to minimize the purchase cost of additional energy from the grid. Ancillary services (e.g. load shifting) can also be offered to the distribution network operators in order to reduce the demand during the peak hours and utilise the off-peak hours for the EV charging (valley-fill). The EV charging demand is controlled in an indirect manner by adopting a dynamic virtual pricing mechanism according to the forecasted EV charging demand and local renewable generation production. In the proposed pricing scheme, the EV/DG aggregator's objective is achieved by assigning low virtual price values to the preferred hours for EV charging, and higher virtual price values to hours where EV charging should be avoided. According to the charging demand, these price values are constantly updated to ensure that the objective is achieved.

The EV agents are entities representing the EV owner's rational behaviour. Their objective is to minimize their individual virtual charging cost, according to the virtual price values. To this end, the EV agents define their charging schedules so that they charge at the cheapest hours. Although there is not a direct interaction between them, one EV agent's charging schedule affects the virtual price values for the other EV agents, and thus their interdependence is indirect. In reality, it is unlikely that all EV owners will participate in such management scheme at all times slots. The flexibility of EV charging demand should not be taken for granted. To reflect this realistic characteristic of future EV fleets, in the adopted charging management framework the EV agents are classified as Responsive and Unresponsive to the pricing signals. Responsive EV agents are the ones that respond rationally to the pricing signals, whereas Unresponsive EV agents define their charging schedule regardless the cost.

2.2. Charging control strategy

The EV/DG aggregator makes profit by providing valley-filling services to the distribution network operator. Its revenues are also increased when the charging energy demand is supplied from (owned) local renewable energy sources. In this context, the EV/DG aggregator sets a dynamic pricing strategy so that the energy demand valleys are used for the EV charging, and when available, the owned renewable energy generation supplies the EV charging demand. In this paper, the objective of the EV/DG aggregator is to achieve a flat net demand profile by utilising the flexibility from Responsive EV agents and the local renewable energy generation. The realistic market arrangements (contractual agreements, energy trading, market participation, etc.) of the aggregator are not investigated in this paper.

The pricing policy considers the technical constraints of the downstream network (MV/LV transformer, LV feeders). The EV/DG aggregator prevents the violation of operational limits by modifying the virtual prices based on the network's stress level.

The Responsive EV agents adjust their charging schedule to the lowest virtual prices, trying to reduce their own individual virtual charging cost. In case of a fixed price curve, the charging demand of all the Responsive EV agents would coincide during the cheapest hours, resulting in a new peak. To avoid this, the EV/DG aggregator adopts a dynamic pricing strategy where the virtual price values are updated sequentially, after the scheduling process of each Responsive EV agent. Fig. 1 shows the resulting demand curve after a fixed and dynamic pricing strategy.

In addition, the effectiveness of the control scheme is significantly affected by the Unresponsive EV agents. The inflexible charging demand from the Unresponsive EV agents change the shape of the total demand curve, and is considered when setting the virtual prices, otherwise the allocation of the flexible EV charging demand is not optimal. This behaviour is explained with an example. A mixture of Responsive and Unresponsive EV agents is assumed and their arrival and departures times are shown in Fig. 2a. An abnormal event occurs at 10:00, when a number of Unresponsive EV agents connected to the charging stations require charging for a short period of time. Without prior knowledge of this abnormal event, the EV/DG aggregator does not adjust the virtual prices accordingly, and the Responsive EV agents schedule their charging in a non-optimal fashion (Fig. 2b and c). To the best of the authors' knowledge, this example indicates the weakness of the majority of the control strategies proposed in the literature.

If the abnormal event is known a priori, the virtual prices could be modified to reflect the new shape of the demand curve. As a consequence of this change the Responsive EV agents charge in an optimal fashion. Therefore, forecasting the demand from Unresponsive EV is critical for the effectiveness of the control scheme. In the adopted control strategy, the EV/DG aggregator forecasts the charging demand from Unresponsive EV agents, and adjusts the virtual prices accordingly.

To maximize its profit, the EV/DG aggregator tries to satisfy the EV charging demand with the local owned renewable energy generation. To this end, it forecasts the next-day's DG generation and adjusts the virtual prices accordingly. By setting lower charging cost when DGs are expected to be available, the EV/DG aggregator incentivizes the Responsive EV agents to consume the DG generation locally.

However, the virtual price values depend on the accuracy of the forecasts (both demand and DG generation). An inaccurate forecast results in profit loss for the EV/DG aggregator as the scheduling solution is not optimal at the end of the day. Therefore, this control strategy considers two operational modes, namely normal and emergency. During normal operation, the forecasts are accurate and the charging schedules are executed exactly as planned. In case of an error in the demand or generation forecast, an emergency mechanism is activated for the current time-step. The EV/DG aggregator calculates the new virtual price values according to the actual demand and generation of the current time-step. The connected Responsive EV agents modify their charging schedule, following the updated virtual prices. This is a sequential process, and the virtual values are updated after "rescheduling" each Responsive EV agent. The emergency operation terminates when

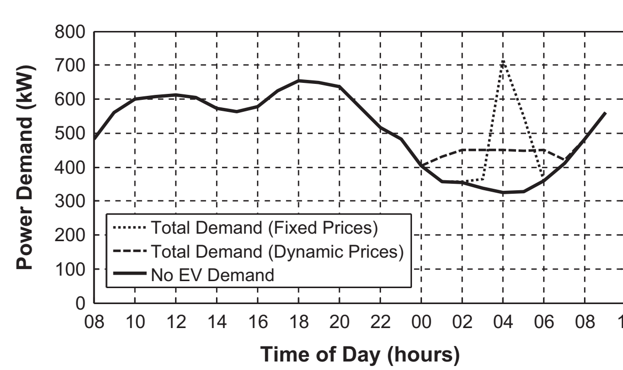

Fig. 1. Fixed charging strategy versus Dynamic Pricing Policy Strategy.

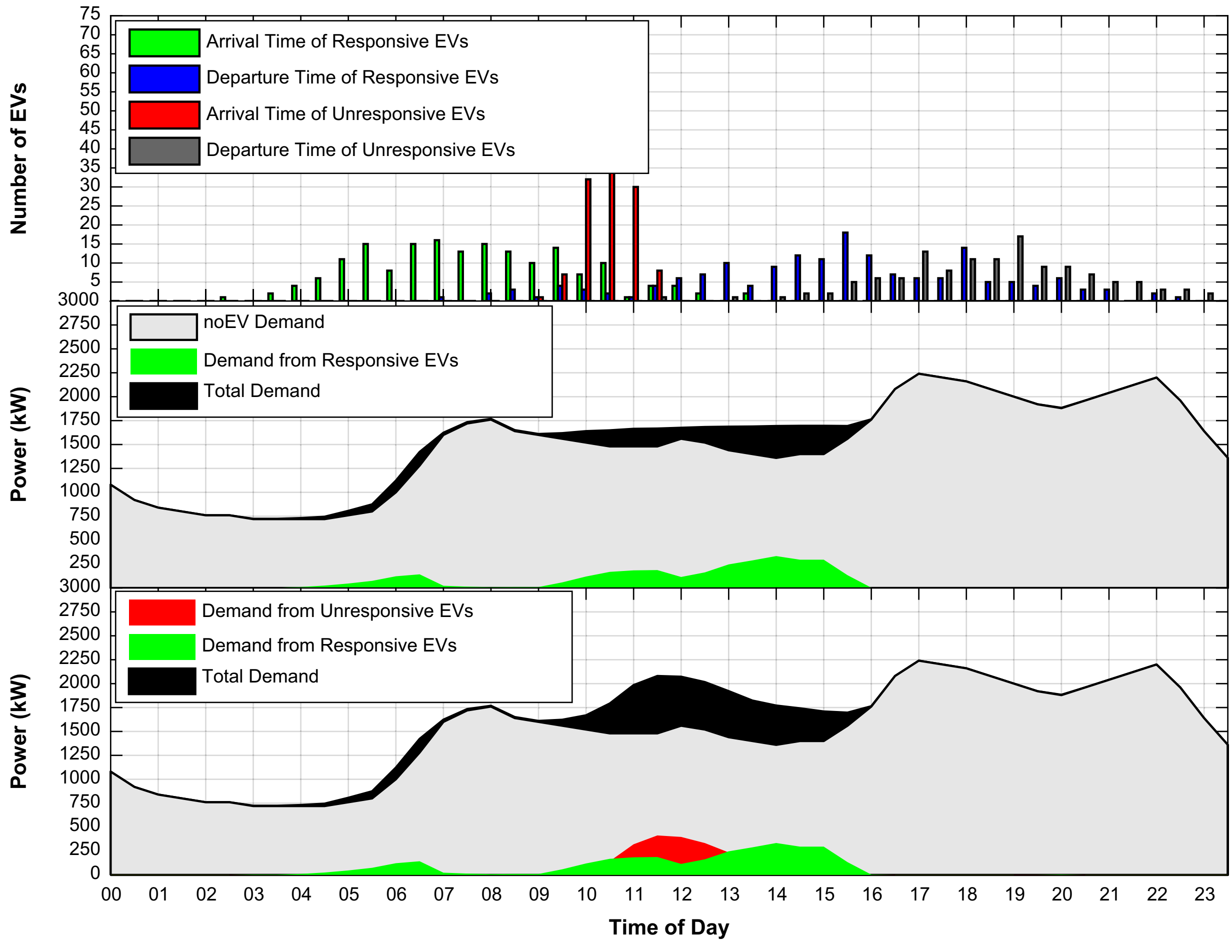

Fig. 2. EV Management without forecasting the demand from Unresponsive EV agents.

the charging demand is again optimally scheduled, based on the new condition of the system. To ensure the participation of Responsive EV agents in this emergency operation, additional incentives are given (e.g. the rescheduled charging demand is not charged). This feature can be utilised to offer demand response services to distribution network operators, e.g. reduce the charging demand during a certain period. Additional contractual agreements should be in place, but the regulatory and contractual aspects are not in the scope of this paper.

2.3. Charging control model

The charging control model follows the multi-agent system architecture. Each entity is modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. All the agents exist in an environment where time is measured in time-steps. During one time-step, an agent either performs a set of actions or waits for a triggering signal from another agent. A sequence of six operational phases occurs in every time-step, namely Initial, Forecasting, Planning, Normal, Emergency and Final.

In the *Initial Phase* the EV/DG aggregator decides whether a new forecast for the demand of Unresponsive EV and the renewable generation is required. The *Forecasting Phase* is only executed on the first time-step of every 24 h, and thus during *Initial Phase* the EV/DG aggregator evaluates the current time-step. At the same time, the EV agent compares the current time-step with its connection time-step in order to decide its next action. In case the current time-step is equal to the connection time-step the EV agent enters its *Planning Phase*, otherwise it enters the *Normal Phase*.

During *Forecasting Phase*, the EV/DG aggregator forecasts the two days-ahead demand of Unresponsive EV and renewable generation for every LV feeder of the corresponding MV/LV transformer in a time-step resolution.

Forecasting the arrival and departure times of Responsive EV agents is not considered in this model. The EV charging demand from the Responsive EV agents does not constitute a risk for the normal operation of the distribution network because this demand is considered controllable. Therefore, it is more important to forecast the non-controllable demand from the Unresponsive EV agents due to the risks and uncertainties related to this inflexible demand.

The forecast is carried out with a two-day time horizon because the EV are assumed to depart in maximum 24 h. If the EV are staying for a longer period of time before departure, the forecasting horizon should be increased. This is seen as a limitation of the model because the EV/DG aggregator must have information about the future state of the system even in the marginal cases (e.g. an EV agent connects at 23:00 with the departure time in 24 h). The forecast model described in [58] is implemented, based on Support Vector Machines and trained using historical data. The historical data contain information about the charging demand from Unresponsive EV and the renewable generation profile. Once the forecasts are available, the EV/DG aggregator uses a typical NoEV demand profile (It is assumed to be provided by the distribution network operator) for every LV feeder to calculate the total scheduled demand of the next day. Assuming that the day is divided in N

time-steps, an array of N values was created for every LV feeder (T_{sch_DMD}). The array contains the total scheduled demand for every time-step k, and was calculated using Eq. (1):

$$T_{sch\_DMD}^{k,f} = F_{UnrespEV}^{k,f} - F_{DER}^{k,f} + S_{\mathrm{Re}\ spEV}^{k,f} + F_{noEV}^{k,f} \tag{1}$$

where:

$k = 1\ldots N$

$f = 1\ldots$Number of LV feeders on MV/LV transformer.

$F_{UnrespEV}^{k,f}$ is the forecasted charging demand from Unresponsive EV for the time-step k.

$F_{DER}^{k,f}$ is the forecasted renewable generation for the time-step k.

$S_{\mathrm{Resp}EV}^{k,f}$ is the total scheduled charging demand of Responsive EV for the time-step k.

$F_{noEV}^{k,f}$ is the forecasted NoEV demand for the time-step k.

Based on the total scheduled demand, the N virtual prices were calculated. A simple pricing mechanism was applied, where the virtual prices were defined in a way that they reflect the EV/DG aggregator's preference for EV charging demand in a certain time-step (valley filling strategy). The EV/DG aggregator decreases the virtual cost of charging during the time-steps with low expected demand, incentivising the EV agents to charge accordingly. The pricing formula is presented in Eq. (2).

$$VP_{k,f} = \frac{T_{sch\_DMD}^{k,f}}{P_f} \cdot w \tag{2}$$

where

P_f is the nominal thermal power limit of the corresponding LV feeder.

w is a profit factor related to the contractual agreement between the EV/DG aggregator and the EV agents.

The virtual prices represent the proportion of the total scheduled charging demand in the total nominal thermal power limit of the corresponding feeder. When the scheduled demand in a feeder is expected to be high, the virtual prices are increased accordingly to discourage EV agents to charge at those times.

The profit factor w does not affect the behaviour of the model, but is related to the revenue targets of the EV/DG aggregator. When the profit factor is equal to one, the virtual price cost increases linearly. If a quadratic function is used to describe the profit factor, the virtual prices are modified non-uniformly. Therefore, the profit factor is a way to extend this conceptual design according to the contractual agreements between the EV/DG aggregator and the EV agents. However, the investigation of these agreements is out of the scope of this paper and thus the factor w is assumed to be equal to one.

In case there are new arrivals or connections of EV agents, the agents enter in the *Planning Phase*. A queue is created (Schedule Queue) containing all the EV agents that have just connected to their charging stations. The EV agents of Schedule Queue solve their scheduling problem on a first-come first-served sequence according to the virtual prices sent from the EV/DG aggregator. The scheduling problem that each EV agent solves is described with Eqs. (3)–(5).

$$\min \sum_{t_n}^{t_n+d_n} P_n(t) \cdot VP_{k,f}(t) \tag{3}$$

Subject to:

$$\sum_{t_n}^{t_n+d_n} P_n(t) = (SOC_{final_n} - SOC_{in_n}) \frac{C_{bat_n}}{\delta_{eff_n}} \tag{4}$$

$$P_n(t) \leqslant P_{ch.nom_n} \tag{5}$$

where

t_n is the connection time of EV agent n to feeder f.

d_n is the charging duration of EV agent n.

$P_n(t)$ is the instantaneous charging power demand of EV agent n.

$VP_{k,f}(t)$ is the virtual cost value of each time step k.

SOC_{final_n} is the desired SOC of EV agent n.

SOC_{in_n} is the initial SOC of EV agent n.

C_{bat_n} is the battery capacity of EV agent n.

δ_{eff_n} is the efficiency of the charging station .

$P_{ch.nom_n}$ is the nominal power rate of the charging station.

Eq. (4) expresses the energy requirements of EV agent n. These requirements are satisfied during the connection period $[t_n, t_n + d_n]$. The instantaneous charging power $P_n(t)$ must not exceed the power rating of the charging station ($P_{ch.nomn}$) for every t, as described in Eq. (5). Once the EV agent defines its charging schedule, it informs the EV/DG aggregator and leaves the Schedule Queue. When the EV/DG aggregator receives a charging schedule from an EV agent, it updates the total schedule demand (T_{sch_DMD}) of the corresponding feeder. The virtual price values are recalculated according to the updated T_{sch_DMD}, waiting for the next EV agent.

The sequential update of the virtual prices has advantages compared to other approaches presented in the literature. In [59], the control signals are updated simultaneously for all EV increasing the communication and computational complexity of the charging scheduling problem. However, using the sequential price update method, the virtual prices need to be updated after the charging request of each Responsive EV agent. These are transmitted only to the next EV in the Schedule Queue. This approach reduces the communication requirements as well as the computation complexity since the optimization problem is solved individually by each EV agent.

In case there are no EV agents in the *Planning Phase*, the *Normal Phase* follows. The EV/DG aggregator monitors the actual NoEV demand, the demand from Unresponsive EV agents and the renewable energy generation for the current time-step. In order to check for possible violations of the network technical constraints, power flow analysis is performed considering the scheduled EV charging demand (from Responsive EV agents) and the monitored information (real time power demand). In case there are no violations or forecasting errors, the EV agents execute their charging schedule for the current time-step. If the technical constraints (transformer nominal ratings, voltage statutory limits, line thermal limits) are violated, the EV/DG aggregator transmits an emergency signal to all connected Responsive EV agents. The EV charging schedule is not executed, and the *Emergency Phase* begins. If the forecast is inaccurate, the *Emergency Phase* does not necessarily begin. The *Emergency Phase* always begin when a violation of the technical network constraints is expected to occur.

A Reschedule Queue is created with the Responsive EV agents that are connected in that time-step. The EV/DG aggregator calculates the amount of EV charging demand that needs to be rescheduled (P_{rsch}) in order to eliminate the problem and updates the virtual prices accordingly. The EV agents reschedule their charging demand for the remaining period before their departure (including the current time-step) using Eqs. (3)–(5) sequentially. After its reschedule, each EV agent updates the total scheduled charging demand of Responsive EV ($S_{\mathrm{Re}\ sp}^{k}$) and leaves the Reschedule Queue. When an EV agent leaves the Reschedule Queue, the EV/DG aggregator updates the Total Scheduled Demand (T_{sch_DMD}) and re-evaluates the emergency condition. If the problem remains, the P_{rsch} is recalculated along with new virtual prices, and the procedure is repeated for the next EV agent in the Reschedule Queue.

The procedure is terminated when either P_{rsch} is equal to zero, or the Reschedule Queue is empty.

The adopted approach for the Emergency Phase is different from the rolling-scheduling method presented in [59]. In the rolling-scheduling (or receding horizon) approach the EV charging scheduling is repeated after each time step in order to account for updated forecasts. In the proposed charging control model, the forecasts are carried out on the first time-step of every 24 h. This results in lower computation complexity as the charging model is required to provide a forecast in longer periods. However, this is a trade-off between the forecast effort and the forecast accuracy. A limitation of the proposed approach is that less frequent forecasts lead to less forecast accuracy.

During *Final Phase*, the EV agents compare the current time-step with their departure time-step ($t_n + d_n$), in order to either disconnect or repeat the operation in the following time-step. At the same time, the EV/DG aggregator returns to its initial state.

All the actions of the EV/DG aggregator agent and the EV agents during one time-step are presented in Fig. 3.

3. Experimental results

3.1. General set up

The control model was experimentally demonstrated at the Electric Energy Systems Laboratory hosted at the National Technical University of Athens (NTUA). The Model-In-the-Loop (MIL) technique is used to demonstrate the EV charging control model under real time conditions. MIL enables the interconnection of a software model and hardware component, identifying their potential interactions and demonstrating the performance of the computer model without increasing the implementation costs. According to [60–63], MIL is defined as a Hardware-in-the-Loop (HIL) testing technique with partially real and virtual (real time software program) test specimens. Hardware-in-the-Loop (HIL) simulation is an approach where physical equipment is connected to a simulated system. This technique is used to test equipment (Hardware under Test – HuT) under real time operation conditions, approaching real life system conditions. Fig. 4 shows a diagram depicting the MIL paradigm followed in the experiments.

The hardware components include a Real Time Digital Simulator (RTDS) and a PV inverter whereas the charging control model is hosted on a personal computer. RTDS is a fully digital device suitable for simulating electrical power systems and networks in real time. It is used to solve power system equations fast enough to generate realistic output conditions approaching the actual operating conditions of a network. The main user's interface with the RTDS hardware is RSCAD which is used to support the design, implementation and analysis of the HIL test. The RTDS used in this setup, comprises several processing cards operating in parallel as well as various digital and analogue inputs and outputs so as to interact with the charging control model in a time step of 0.5 s.

The typical 33/11/0.4 kV UK generic distribution network model [57] was simulated in RSCAD. The system is comprised of a 33 kV three-phase source, two 33/11.5 kV 15 MV A transformers with on-line-tap-changer and an 11 kV substation with five 11 kV outgoing MV feeders. Each 11 kV feeder supplies eight 11/0.433 kV 500 kV A distributed transformers with off-line-tap-changer. Each MV/LV transformer has four LV feeders, and each LV feeder provides energy to 96 customers. The network's topology is shown in Fig. 5. Real-time PV generation values were obtained from 10 PV modules (110 W each) through the SMA Sunny Boy inverter (1100 W) and were used as inputs to the charging control model.

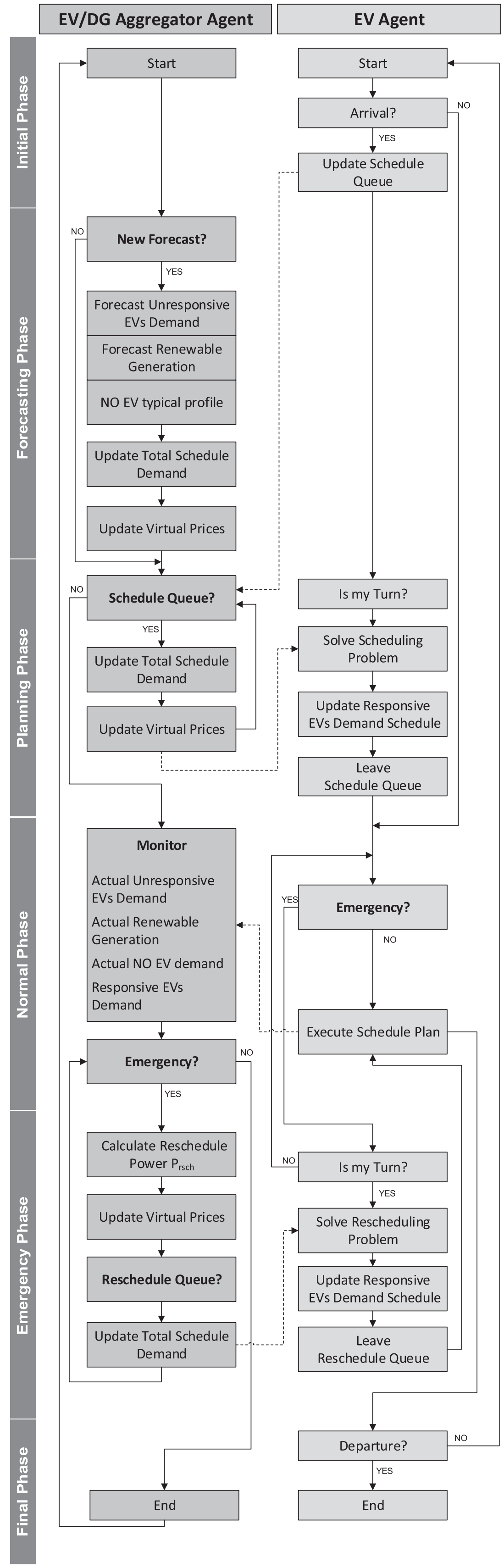

Fig. 3. Flowchart of EV Charging Control Model.

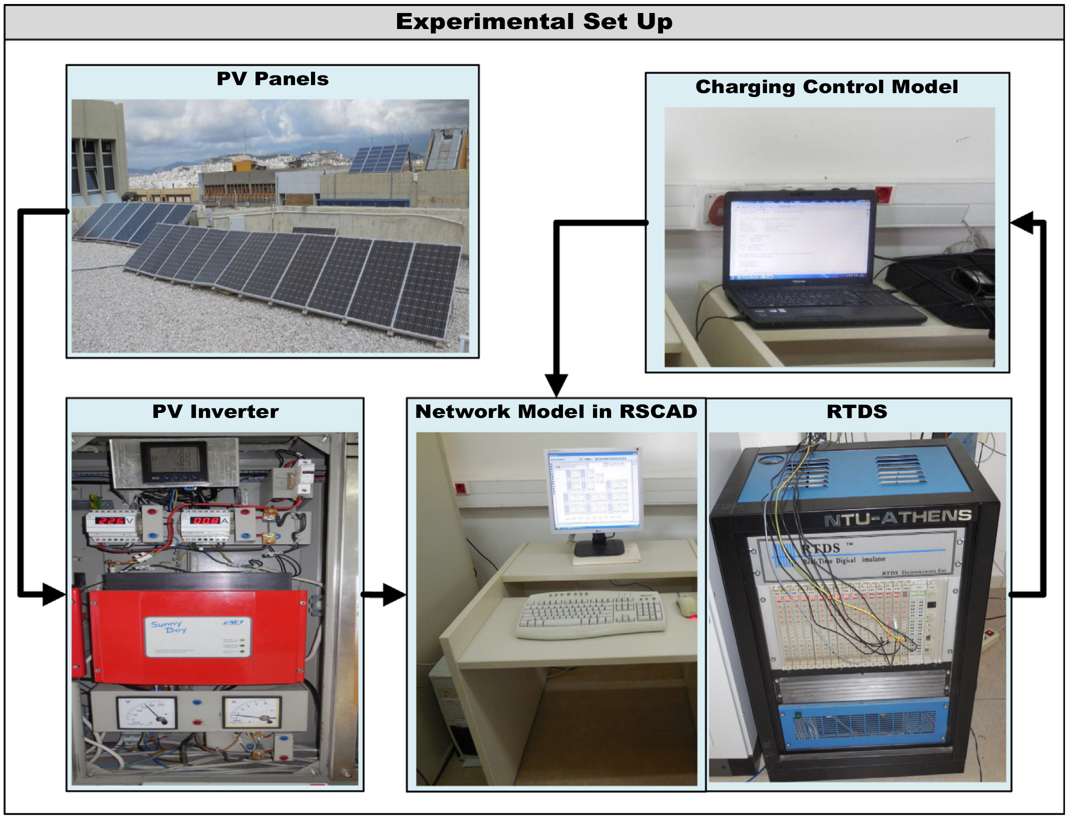

Fig. 4. Experiment structure.

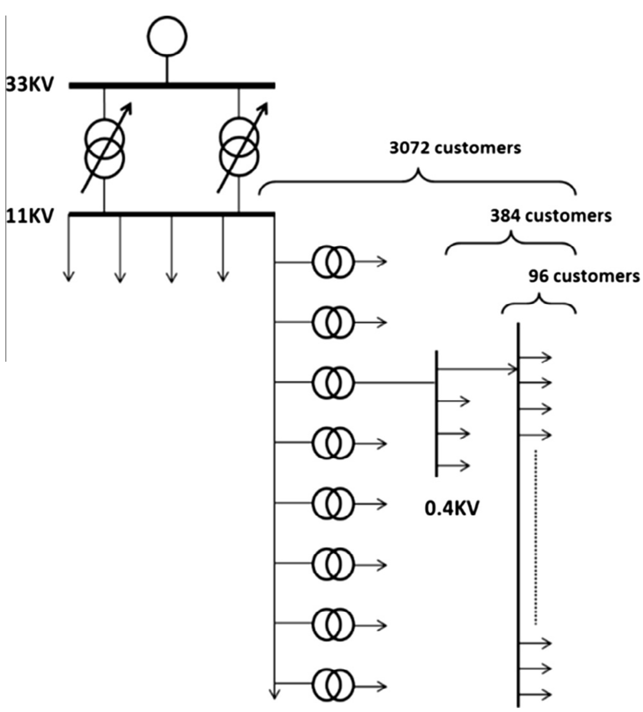

Fig. 5. The typical 33/11/0.4 kV UK generic distribution network.

Three case studies were implemented to demonstrate the performance of the charging control model under different operating conditions. The experiments allowed the examination of the closed-loop system consisted of the PVs, the simulated electric power network and the charging control model.

3.2. Locating the EV/DG aggregator agent

This case study investigates the impact of EV charging on the UK distribution network considering two different locations for the EV/DG Aggregator. In the proposed control strategy the EV/DG aggregator was located at the MV/LV transformer, responsible for 384 customers equally allocated to 4 LV feeders. In this case, the virtual prices were calculated according to the demand of each LV feeder. An alternative location was also studied, where the EV/DG aggregator was located before the MV feeder, responsible for 3072 customers (8 MV/LV transformers). In this case, the EV/DG aggregator calculated the virtual prices according to the demand of the MV feeder. The control strategy and the behaviour of the agents were considered the same; the only difference between the two cases was the location of the EV/DG aggregator and the calculation of the pricing signals.

The assumptions are presented in Table 1. In the residential charging scenario the EV agents are charging at home after work. To capture the stochasticity of the travel patterns of the EV agents, normal distributions were used to describe the arrival and departure times of the EV agents as well as the initial and the final (desired) battery SOC for each EV agent. Their mean μ and standard deviation (σ) are shown in Table 1. According to [64], an EV uptake level of 20% is considered as Business as Usual Scenario. Therefore, a number of 640 EV agents was considered, equally distributed to the 32 LV feeders. Non EV demand curves were obtained from [65] for a typical Spring weekday. The assumptions used to describe this scenario does not affect the general performance of the model, although they affect the level of the benefit from the EV charging coordination. If the times for charging requests from Responsive and Unresponsive EV agents does not coincide, there is less flexibility from Responsive EV agents to flatten the demand from the Unresponsive EV agents.

Table 1
Scenario assumptions.

Variable	Mean value (μ)	Standard deviation (σ)
Number of Responsive EV agents	640	–
Number of Unresponsive EV agents	0	–
Arrival time of Responsive EV agents (h)	18:00	2
Departure time of Responsive EV agents (h)	08:00	2
Power of EV charging stations (kW)	3.6	–
Efficiency of charging station (δ_{eff})	0.8	–
Battery capacity (kW h)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10

Fig. 6 presents the results for the two different cases. Fig. 6a is related to the case where the EV/DG aggregator was located at the MV feeder. The results when the EV/DG aggregator was located at the MV/LV transformer are shown in Fig. 6b. On the middle and bottom row of Fig. 6, the thin grey lines represent the eight transformers and 32 LV feeders of the typical 33/11/0.4 kV UK generic distribution network model respectively.

In both cases the EV agents charge during off-peak hours, achieving a valley-filling effect at the demand curve of the MV feeder. However, when the prices were calculated according to the power demand of MV feeder (Fig. 6a), the operation of the downstream network was not optimal. The demand profiles of the MV/LV transformers and the corresponding LV feeders are fluctuating during the EV charging period. On the other hand, when the EV/DG aggregator was located at the MV/LV transformer and the virtual prices were calculated according to the demand of each LV feeder, the demand profiles show a significant improvement. The demand fluctuation during the EV charging period was reduced, resulting in a flattened demand curve at all voltage levels. The standard deviation and the average demand in each time step is used to compare the fluctuation between the two cases. The results are summarized in Table 2.

Although the average demand is almost the same in both cases, the standard deviation is double when the EV/DG aggregator agent is located at the MV feeder. Less fluctuation in the demand results in less fluctuation in the voltage profiles of the MV/LV transformers (LV bus side), indicating an improved operation of the network.

3.3. Importance of forecasting the charging demand of Unresponsive EV Agents

In the proposed control strategy the EV/DG aggregator forecasts the two days ahead charging demand for Unresponsive EV agents. In this case study, the performance of the proposed control model was compared with the case when the EV/DG aggregator does not have the capability to provide forecasts of the charging demand from Unresponsive EV agents. A residential EV charging scenario was also considered in this case study. To highlight the importance of the forecasting actions, an EV uptake level of 60% (Extreme

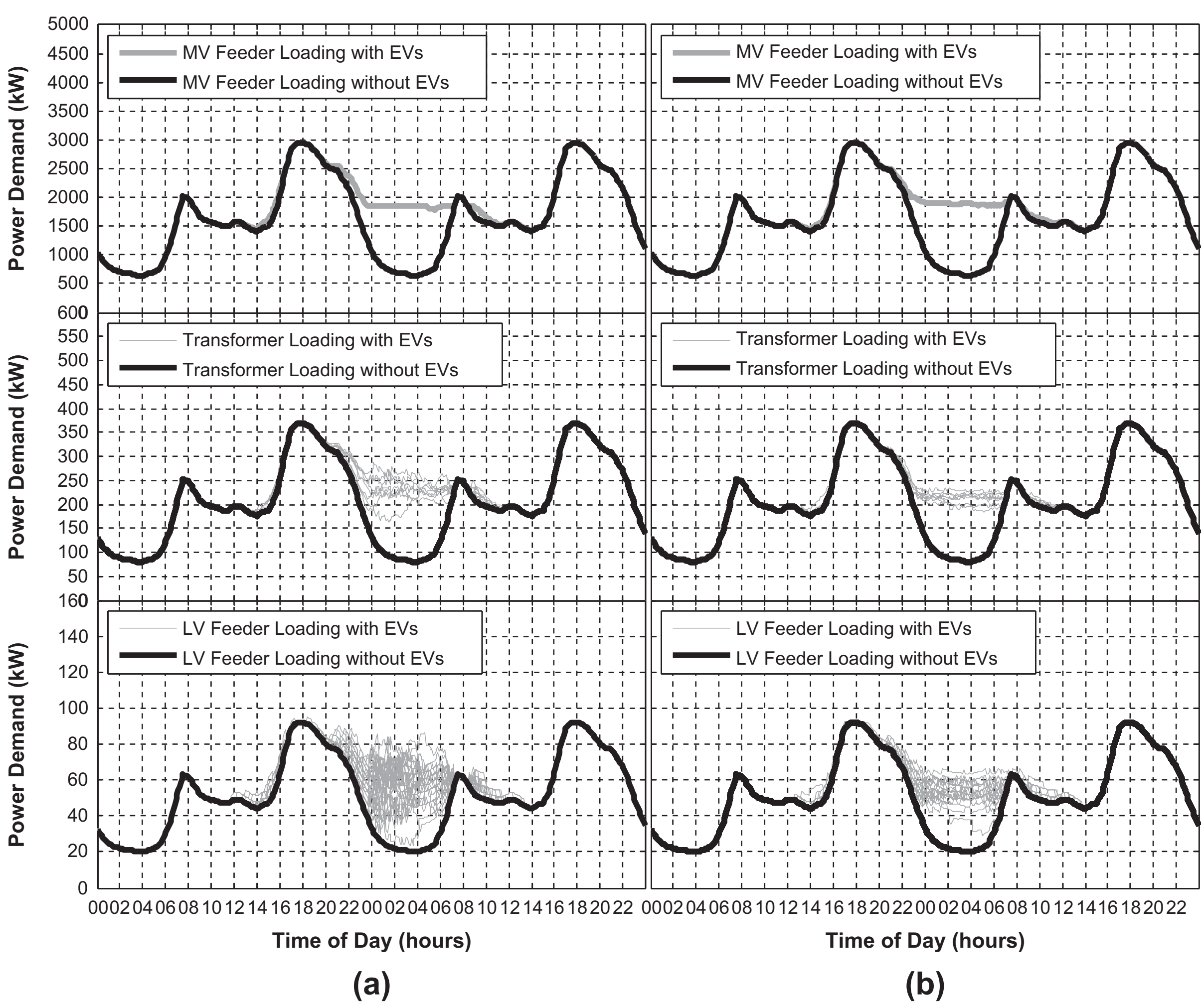

Fig. 6. Power Demand when the location of the EV/DG aggregator agent is at the (a) MV feeder (b) MV/LV transformers.

Table 2
Comparison of the two different cases.

Index	EV/DG aggregator agent is at the MV feeder	EV/DG aggregator agent is at the MV/LV transformers	Difference between two cases
Maximum Standard Deviation among all time steps	12.66	6.34	50%
Average Standard Deviation among all time steps	2.45	1.48	39%
Average Demand among all time steps	57.01	55.99	2%

Table 3
Scenario assumptions.

Variable	Mean value (μ)	Standard deviation (σ)
Number of Responsive EV agents	1472	–
Number of Unresponsive EV agents	352	–
Arrival time of Responsive EV agents (h)	18:00	2
Departure time of Responsive EV agents (h)	08:00	2
Arrival time of Unresponsive EV agents (h)	21:30	1
Departure time of Unresponsive EV agents (h)	08:00	2
Power of EV charging stations (kW)	3.6	–
Efficiency of charging station (δ_{eff})	0.8	–
Battery capacity (kW h)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10

Scenario of [64]) was considered. According to this uptake level a total number of 1824 EV agents was used with 352 Unresponsive EV agents and 1472 Responsive EV agents. An abnormal event was assumed to occur around 21:30, when all Unresponsive EV agents arrived to their charging station and start charging. A 100% accurate forecast of this event was assumed to be available, so that the EV/DG aggregator can adjust the virtual prices accordingly. The assumptions are presented in Table 3.

Fig. 7 presents the power demand of the MV/LV transformer and its corresponding LV feeders in both cases. The results show that due to the EV load forecasting capability of the EV/DG aggregator, the Responsive EV agents are modifying their charging schedules in order to reduce the impact of Unresponsive EV charging on the demand curve. The charging demand of the Responsive EV was adapted to the Unresponsive EV charging demand so that their aggregation results in a valley filling effect on the Non EV demand curve. In most cases, this adaptive behaviour of Responsive EV leads to a reduction of the aggregated charging demand peak.

The level of this reduction was affected by the charging scenario. High levels of Unresponsive EV lead to inflexible demand, thus the capability of the proposed control model to reduce the peak charging demand was limited. Moreover, the accuracy of the forecast affects the final result, as the virtual prices would then be calculated based on incorrect estimation of the power demand. Finally, if the charging times of Responsive and Unresponsive EV agents do not coincide (e.g. the responsible EV agents charge at night and the Unresponsive EV agents charge during the morning), the aggregated charging demand cannot be modified.

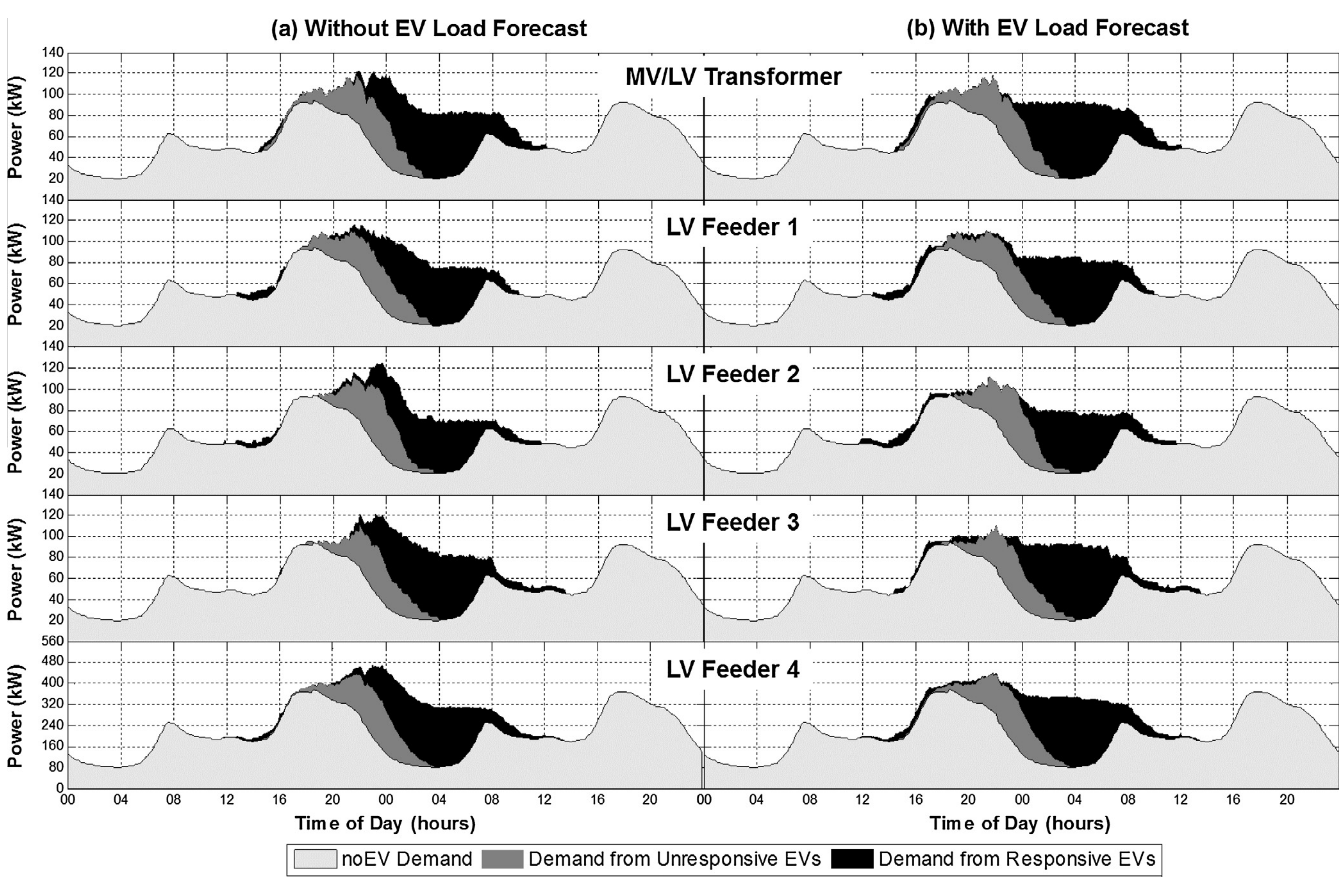

Fig. 7. Power Demand for the MV/LV transformer and the corresponding LV feeders when the forecasting capability of the EV/DG aggregator agent is (a) disabled (b) enabled.

Table 4
Scenario Assumptions.

Variable	Mean value (μ)	Standard deviation (σ)
Number of EV agents	640	–
Arrival time of EV agents (h)	08:00	2
Departure time of EV agents (h)	17:00	2
Power of EV charging stations (kW)	3.6	–
Efficiency of charging station (δ_{eff})	0.8	–
Battery capacity (kW h)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10
PV generation capacity (kW)	132	–

3.4. Charge preferentially from renewables

To maximize its profit, the EV/DG aggregator tries to satisfy the EV charging demand with the local owned renewable energy generation. This case study investigates the capability of both Responsive and Unresponsive EV agents to adapt their charging schedules to the local DG generation. The PV panels of the Microgrid Laboratory of NTUA were used as local DG generation connected to one MV/LV transformer. Their capacity of 1.1 kW was scaled up to 132 kW in order to represent a PV park of considerable size. Historical data of one year were used to forecast the two days ahead PV generation. A morning charging scenario was assumed, where the EV agents charge during the day. The EV/DG aggregator agent acquired real time PV generation values from the PV inverter, and when necessary entered in the *Emergency Phase*. During this phase, the Responsive EV agents modified their charging schedule,

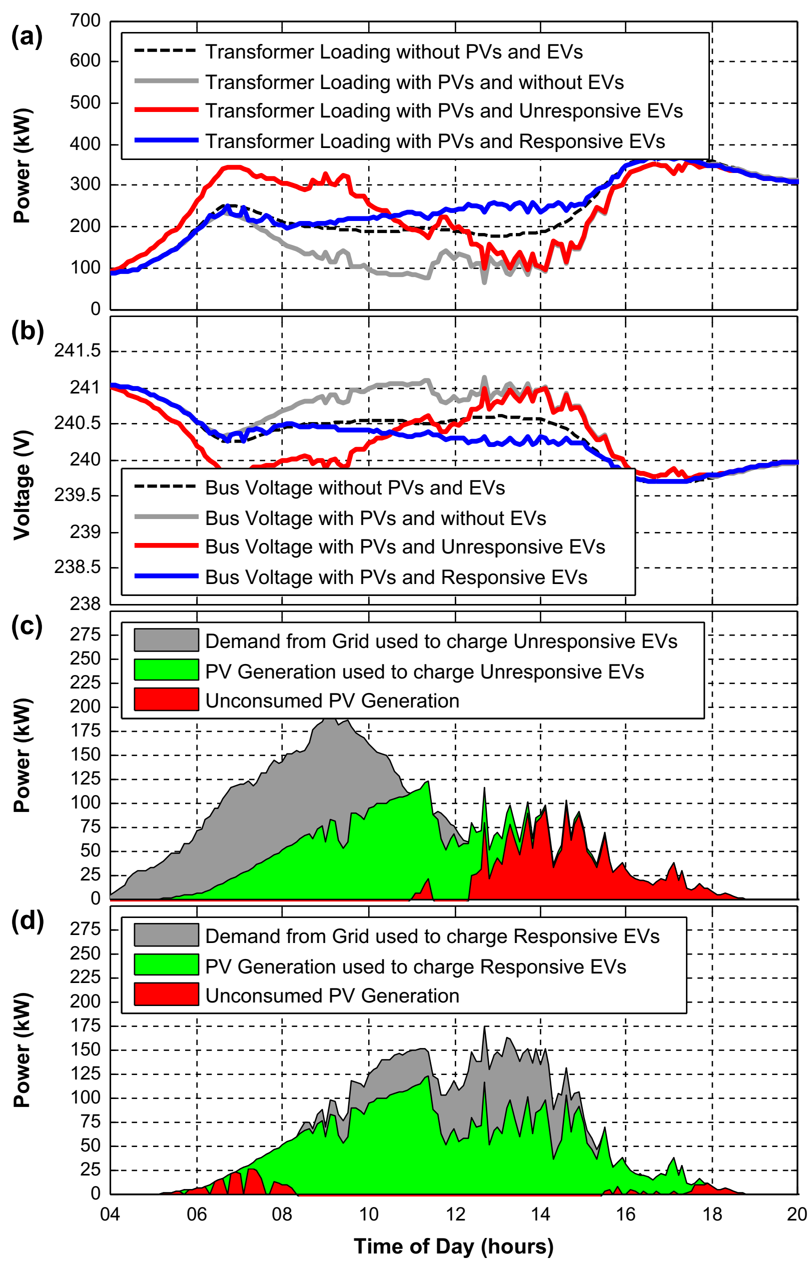

Fig. 8. (a) Power Demand for the MV/LV transformer, (b) Voltage Profile at the LV bus level, (c) Charging Demand from Unresponsive EV agents, (d) Charging Demand from Responsive EV agents.

in order to consume the local DG generation. Table 4 presents the assumptions for this case study.

Fig. 8a and b presents the MV/LV transformer loading and voltage of LV bus in two different cases. In the case where PVs and Unresponsive EV agents were considered, a new peak was created on the power demand curve of the MV/LV transformer. However, in the case where PVs and Responsive EV agents were considered, the fluctuation in the power demand curve of the MV/LV transformer was decreased without creating a new peak. Similarly, the LV bus voltage shows less fluctuation when the Responsive EV agents adapt their charging demand according to the PV generation profile.

Fig. 8c and d shows the proportion of the consumed PV generation for EV charging from Unresponsive and Responsive EV agents respectively. According to Fig. 8c, the 64.73% of the PV generation was used to charge the batteries of the Unresponsive EV agents. However, when the EV agents were Responsive, they adjusted their charging schedules according to the times with high PV generation, utilising the 94.41% of the PV generation.

In the case with Unresponsive EV agents, the proportion of their charging demand in the PV generation was depended on the charging scenario. For example, while the EV charging demand coincides with the PV generation, this proportion increases. Therefore, unless a coincidence between EV charging demand from Unresponsive EV agents and renewable generation exists, they charge without considering the times with renewable generation.

As seen from Fig. 8c, an unexpected drop in the PV generation occurred at around 12:00 due to cloudiness, and the EV agents had to charge using energy from the grid. The Unresponsive EV agents ignored this change and used the energy from the grid for their charging. However, this drop in the PV generation was dealt differently by the Responsive EV agents. Incentivized by the EV/DG aggregator, they entered the *Emergency Phase* and rescheduled their charging demand in a way that the required energy from the grid was consumed in a valley-filling fashion. The results demonstrated the adaptive behaviour of Responsive EV agents and their preference to charge from renewable energy sources.

4. Conclusions

This research presented a decentralized EV management framework for the EV charging. The architecture followed in this charging control model was based on Multi-Agent Systems. Each entity was modelled as an autonomous agent, interacting with other agents and trying to achieve its own goals. The MAS consisted of an EV/DG aggregator agent and Responsive or Unresponsive EV agents. The EV/DG aggregator agent was responsible to design the appropriate virtual pricing policy so that it can maximize its profit. Responsive EV agents were able to respond rationally to the virtual pricing signals, whereas Unresponsive EV agents were defining their charging schedule regardless the virtual cost.

The feasibility and effectiveness of the control model was experimentally demonstrated in the Electric Energy Systems Laboratory of the NTUA. Three cases studies were presented. The first case study investigated the impact of EV charging on the UK distribution network when the EV/DG Aggregator was located either in the MV/LV transformer or the MV feeder. It was demonstrated that the location of the EV/DG aggregator agent affects the demand and voltage profiles of the LV feeders. The second case study demonstrated the importance of the EV load forecasting in the control strategy. When the EV/DG aggregator has load forecasting capabilities, the Responsive EV agents are adapting their charging schedule to reduce the impact of the Unresponsive EV agents on the demand curve. The third case study tested the capability of Responsive EV agents to charge preferentially from renewable energy sources. The results demonstrated their capability to reschedule their charging demand according to a real time PV generation profile.

Smart management of EVs charging based on aggregation enhanced by EVs load forecasting could be seen as a win–win strategy for both the DNO and the vehicle owners. The "aggregator" is a new market entity which will control multiple EVs. The concepts developed in this work are applied for the development of a cloud-based Virtual Power Plant (VPP) under the Innovate UK – EPSRC "Ebbs and Flows of Energy Systems" project. The charging control model is applied in Manchester Science Park, utilising the flexibility of EV and the local PV generation, in order to decrease the electricity cost of the site.

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