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Management of electric vehicle battery charging in distribution networks with multi-agent systems

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ABSTRACT

An agent-based control system that manages the battery charging of electric vehicles in power distribution networks is presented. The electric vehicle battery charging schedules are calculated according to electricity prices and distribution network technical constraints. The design of the multi-agent system is described. The real-time operation of the multi-agent system was demonstrated in a test-bed of a laboratory micro-grid.

1. Introduction

A high electric vehicle (EV) uptake is expected in the forthcoming years [1]. EV battery charging will increase the electricity demand and distribution networks will be required to cope with this increase [2]. To aggregate EV resources and enable their battery charging management, the control approaches that have been proposed in the literature are: (i) centralised approach such as [3–5] where the system's decision making is implemented in a central coordination unit and (ii) distributed approach such as [6–10] where the system's decision making is distributed among the control units of the system. As reported in [6,7], one of the main drawbacks of centralised control approach is the computational intensity and data transfer for the battery charging management of large populations of EVs.

Distributed control has been identified in [11] as one of the most promising applications of multi-agent system (MAS) in power systems applications, where the main benefits of using MAS are presented as: (i) flexibility, (ii) extensibility, (iii) fault tolerance, (iv) open architectures and (v) distribution. Some practical MAS implementations in power systems including distributed control can be found in [12].

The use of MAS for real-time management of EVs is proposed in the literature for load levelling [6,7], for reducing imbalance costs [8,9] and for the provision of frequency regulation services [10]. This paper contributes to the literature by demonstrating a real-time MAS control approach in which EVs are managed according to electricity prices, technical constraints and having the capability to provide active demand services.

The management framework developed within the European Union (EU) project Mobile Energy Resources in Grids of Electricity (MERGE) [13] was adopted. The operational framework was further developed at Cardiff University within the EU project Distributed Energy Resources Research Infrastructures (DERRI) [14].

2. Multi-agent system description

The MAS has a hierarchical architecture, presented in Fig. 1, and consists of:

- The *electric vehicle aggregator*, which is responsible for the EV battery charging management. The electric vehicle aggregator comprises three types of agents: EV agent, local area agent and coordinator agent. The *EV agent*, located in the EV, sends the

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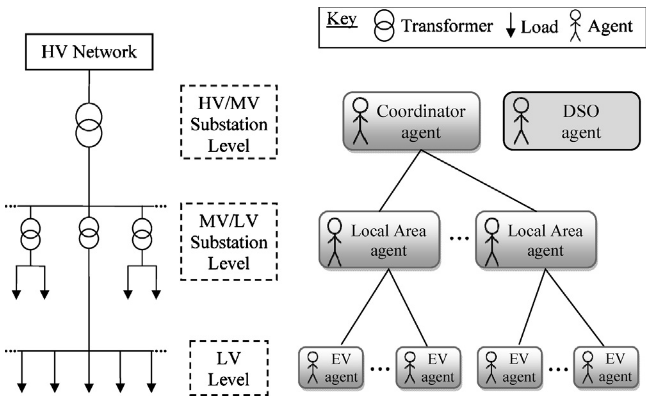


Fig. 1. Multi-agent system hierarchy.

EV owner preferences to the local area agent, and receives the charging set points from the local area agent. The *local area agent*, located at the MV/LV substation level, calculates the optimal battery charging schedules of the EVs and sends the aggregated EV demand to the coordinator agent. The *coordinator agent*, located at the HV/MV substation level, aggregates the demand of the local area agents and sends the aggregated demand to the DSO agent.

- The *distribution system operator* (*DSO*), which is responsible for the operation of the distribution network within technical constraints. It comprises the DSO agent located at the HV/MV substation level. The *DSO agent* validates the EV demand and curtails EV battery charging in case network limits are violated.

2.1. Assumptions

EV batteries are assumed to be charged at constant power rate, i.e. zero or maximum charging power rate (defined by the charging mode used: standard, fast or rapid [15]).

Real-time measurements are monitored by the DSO agent, the technical constraints considered are: steady state voltage limits, transformers loading limits and LV cables loading limits. The electricity prices are made available to the coordinator agent on a day-ahead basis and do not vary based on the demand.

2.2. Time line

The operation of the MAS consists of an operational period (OP) and a scheduling period (SP) at every hourly time interval. The charging set points applied during the operational period of hour $T+1$ are calculated during the scheduling period of hour T.

2.3. DSO network limits matrix and technical validation

The DSO agent calculates the network limits matrix; which consists of the maximum power that can be drawn by the EVs at each LV feeder of the distribution network, during each hour of the day. The concept of the network limits matrix was firstly proposed in the EU project Active Distribution network with full integration of Demand and distributed energy RESourceS (ADDRESS) [16] for distributed energy resources (DERs) market participation and further developed in [2] for EV market participation.

The technical validation of the aggregated EV demand is done by the DSO agent prior to every operational period to ensure the operation within distribution network technical constraints. The DSO agent has the non-EV forecasted demand.

The DSO is assumed to compensate the EV aggregator for the services of EV curtailment and EV demand modification (when the EV demand is not validated) [13].

2.4. Operational modes

In this control approach two operational modes are defined: (i) normal operation, where the distribution network is operated within technical limits and (ii) emergency operation where the voltage limits are violated and/or transformers and cables are overloaded.

3. Normal operation when the network is within technical limits

3.1. Electric vehicle agent

At the beginning of each scheduling period the EV agent sends to the local area agent the following information: (i) the actual state of charge (SoC), (ii) the desired SoC at the end of the charging session, (iii) the connection duration, (iv) the on-board battery charger efficiency, (v) the charging power rate and (vi) the EV battery charging efficiency. At the beginning of every operational period the EV agent receives the charging set point from the local area agent.

3.2. Local area agent

The information received at every scheduling period from the EVs is used by the local area agent to: (i) monitor the EVs' SoC and (ii) deal with possible changes in users' preferences (for example the change in departure time or in final SoC requirements).

EV optimal charging schedules are calculated by the local area agent using the information received at the beginning of each scheduling period from:

- The coordinator agent, which comprises the loading capacity limits contained in the network limits matrix and the electricity prices for each hour.
- The EV agents, which comprises the EV owners' preferences (shown in Section 3.1).

The optimisation software package IBM ILOG CPLEX [17] was used to calculate the optimal charging schedules. The objective function is formulated as follows:

$$\text{minimise}\, Z = \sum_{t=T}^{Tf}\sum_{n=1}^{N} E_{Vn_t} \times p_t \tag{1}$$

where t is the hour, T is the hour of the following operational period, Tf is the final operational period, n is the EV number, N is the total number of EVs managed by the local area agent, E_{Vn_t} is the energy in kWh supplied to EV n during hour t and p_t is the electricity price of the hour t in £/kWh.

Subject to the following constraints:

$$\sum_{t=i_n}^{Tfn} E_{n_t} \geq E_{d_n} \quad \text{for}\, n = \{1, \ldots, N\} \tag{2}$$

$$\sum_{n=1}^{Ns} P_{n_t} \leq L_{s_t} \quad \begin{cases} \text{for}\, t = \{1, \ldots, Tf\} \\ \text{for}\, s = \{1, \ldots, S\} \end{cases} \tag{3}$$

where Tfn is the disconnection hour of EV n, i_n is the connection hour of EV n, E_{n_t} is the energy in kWh stored in the battery of EV n during hour t (energy supplied to EV n multiplied by the battery charging efficiency and the on-board charger efficiency), E_{d_n} is the desired energy in kWh at the end of the charging period of EV n, s is the network feeder, S is the number of feeders, N_s is the total number of EVs connected to feeder s, P_{n_t} is the power rating in kW of EV n for the hour t (defined by the charging mode used) and L_{s_t} is the loading capacity limit in kW at feeder s for the hour t.

Eq. (2) is an inequality in order to ensure convergence in the optimisation since the problem is modelled for mixed integer optimisation with finite horizon of hourly time-steps, i.e. a time interval is assigned to charge or not with a predefined constant power rate.

3.3. Coordinator agent

The coordinator agent acts as an intermediary between the local area agents and the DSO agent during normal operation. At each scheduling period the coordinator agent receives from the local area agents the aggregated EV demand and the EV curtailment factors of the following operational period. The curtailment factors are used by the DSO agent in order to decide which EVs to curtail in case of an emergency situation as defined in Section 4.

The coordinator agent forwards to the DSO agent the EV curtailment factors and the EV aggregated demand for technical validation.

The outcome of the technical validation process received from the DSO agent is sent to the local area agents by the coordinator agent.

3.4. DSO agent

The DSO agent sends on a daily basis the network limits matrix to the coordinator agent. At every scheduling period the DSO agent:

(1) Evaluates, by running a power flow, the aggregated EV demand for the following operational period.
(2a) If the charging set points are validated (i.e. no technical constraints violations are foreseen after running the power flow by the DSO agent), the DSO agent informs the coordinator agent, which informs the local area agents that the charging set points are validated.
(2b) If the charging set points are not validated, the DSO agent updates the network limits matrix and forwards it to the coordinator agent, which in turn sends it to the local area agents. New EV charging schedules are calculated by the local area agents and are sent to the DSO agent through the coordinator agent; the process restarts at (1).

4. Emergency operation when the network is not within technical limits

The DSO agent monitors continuously the network; if a limit breach is detected, the DSO agent curtails the charging of EVs until normal operation conditions are restored. The EVs are curtailed according to their curtailment factor and network location.

The curtailment factors are calculated at each scheduling period by the local area agents. After the optimisation is performed, Eq. (1), the local area agent counts the number of idle assigned time intervals of each EV. EVs with higher amount of idle time intervals will have higher curtailment factors and will be curtailed first in the case of emergency. The curtailment factors ensure that the EV agents curtailed are those with more idle hours scheduled. Having more idle hours scheduled gives the opportunity to the local area agent to re-assign a new charging schedule to the EV agent and satisfy its demand, if curtailed by the DSO agent.

The network location where the emergency is detected will determine the EVs that can be curtailed in order to restore the system to normal operating conditions. For example, if overloading is detected in a transformer, the eligible EVs to be curtailed would be the EVs connected downstream of the overloaded transformer.

5. Demand reduction service provided by the local area agents

In the developed multi-agent system, active demand [16] is provided by the local area agents, after a coordinator agent request for demand reduction at a specific time interval (hour). Active demand services are contracted "*based on estimated consumptions of group of customers*" [18]. A forecasted EV aggregated demand at the coordinator agent and at the local area agents is assumed for the provision of demand reduction services. The total EV demand (kWh) is not reduced; hence a demand reduction at a specific hour implies that the demand is shifted to other hours. The cost of the demand reduction service is defined by the time intervals (hours) to where the demand is displaced to.

5.1. Local area agent

At the beginning of the scheduling period the local area agents receive a message from the coordinator agent requesting a demand reduction for a specific hour (different from the hour of the scheduling period).

The demand reduction calculation is performed by comparing the optimal schedule (Section 3.2) with the *demand reduction schedule* (DRS). The DRS is obtained with the optimisation presented in Section 3.2, i.e. Eqs. (1)–(3), assigning a virtual electricity price of the hour for which the demand reduction is requested, p_t in Eq. (1), higher than the examined pricing time-series. Thus at the specific hour the DRS will have assigned the minimum possible EV load.

The demand reduction offer calculated by the local area agent (comparison of the optimal schedule with the *DRS*) is sent to the Coordinator agent in the form of a matrix, Fig. 2(a). Each row of the matrix contains the number of EVs (N), with their charger power rating (P), which demand is displaced to the same hour (i.e. with the same electricity price, p). In Fig. 2(b) an example is shown of the comparison of the optimal schedule and the DRS, and in Fig. 2(c) the resulting demand reduction matrix.

After receiving the accepted demand reduction (D_a) in kW from the coordinator agent, the local area agent defines its maximum demand (L_{LA}) at the hour for which the reduction was requested (tr) with Eq. (4):

$$L_{LA_{tr}} = D_{fLA_{tr}} - D_{a_{tr}} \tag{4}$$

where tr is the time interval (hour) for which the demand reduction was requested, D_{fLA} is the forecasted EV aggregated demand of the local area agent in kW and D_a is the accepted demand reduction from the coordinator agent in kW.

In order to satisfy the demand reduction accepted by the coordinator agent, the local area agent adds the local area agent maximum demand (L_{LA}) as a constraint in the optimisation procedures of the following scheduling periods with Eq. (5).

$$\sum_{n=1}^{N} P_{n_{tr}} \le L_{LA_{tr}} \tag{5}$$

where P_n is the power rating of each EV n in kW and L_{LA} is the defined maximum demand set by the local area agent after the accepted demand reduction from the coordinator agent, Eq. (4).

5.2. Coordinator agent

Based on the demand reduction matrices received from the local area agents, the coordinator agent calculates the optimal combination in order to achieve the desired demand reduction

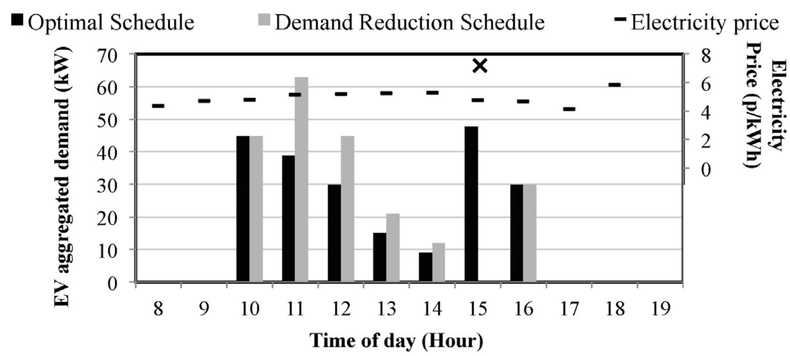
a) Demand reduction matrix

Local Area agent *a*		
Number of EVs (Units)	**Power Rating (kW)**	**Electricity Price*(£/kWh)**
N_{a1}	P_{a1}	p_{a1}
N_{a2}	P_{a2}	p_{a2}
...	...	...
N_{aM}	P_{aM}	p_{aM}

**Electricity price of the hour to where the demand is displaced to.*

b) Example of optimal schedule and demand reduction schedule comparison

(Demand reduction request at hour 9 for hour 15)



× *Virtual electricity price used to obtain the Demand Reduction Schedule*

c) Demand reduction matrix from example b)

Local Area agent *a*		
Number of EVs (Units)	**Power Rating (kW)**	**Electricity Price (p/kWh)**
8	2.99	5.13
5	2.99	5.19
2	2.99	5.27
1	2.99	5.29

Fig. 2. Demand reduction matrix.

at the minimum cost. The objective function is formulated as follows:

$$\text{minimise}\, Z = \sum_{a=1}^{A}\sum_{m=1}^{aM} X_{am} \times P_{am} \times h \times p_{am} \tag{6}$$

where a is the identifier of each local area agent, A is the number of local area agents, m is each of the different offers of the local area agent (each row of the demand reduction matrix, Fig. 2(a)), aM is the number of different offers of each local area agent a (total number of rows of the demand reduction matrix, Fig. 2(a)), p_{am} is the electricity price in £/kWh of the hour to where the demand is displaced to, P_{am} is the power rating in kW, h is the operational period duration in hours and X_{am} (outcome of the optimisation) is the number of EVs with power rating P_{am} and cost of p_{am}.

Subject to the following constraints:

$$X_{am} \leq N_{am} \tag{7}$$

$$\sum_{a=1}^{A}\sum_{m=1}^{aM} (X_{am} \times P_{am}) \geq D_R \tag{8}$$

where N_{am} is the number of EVs (units) offered by the local area agent with a power rating of P_{am} and an associated cost of p_{am} (Fig. 2(a)) and D_R is the targeted demand reduction set by the coordinator agent in kW.

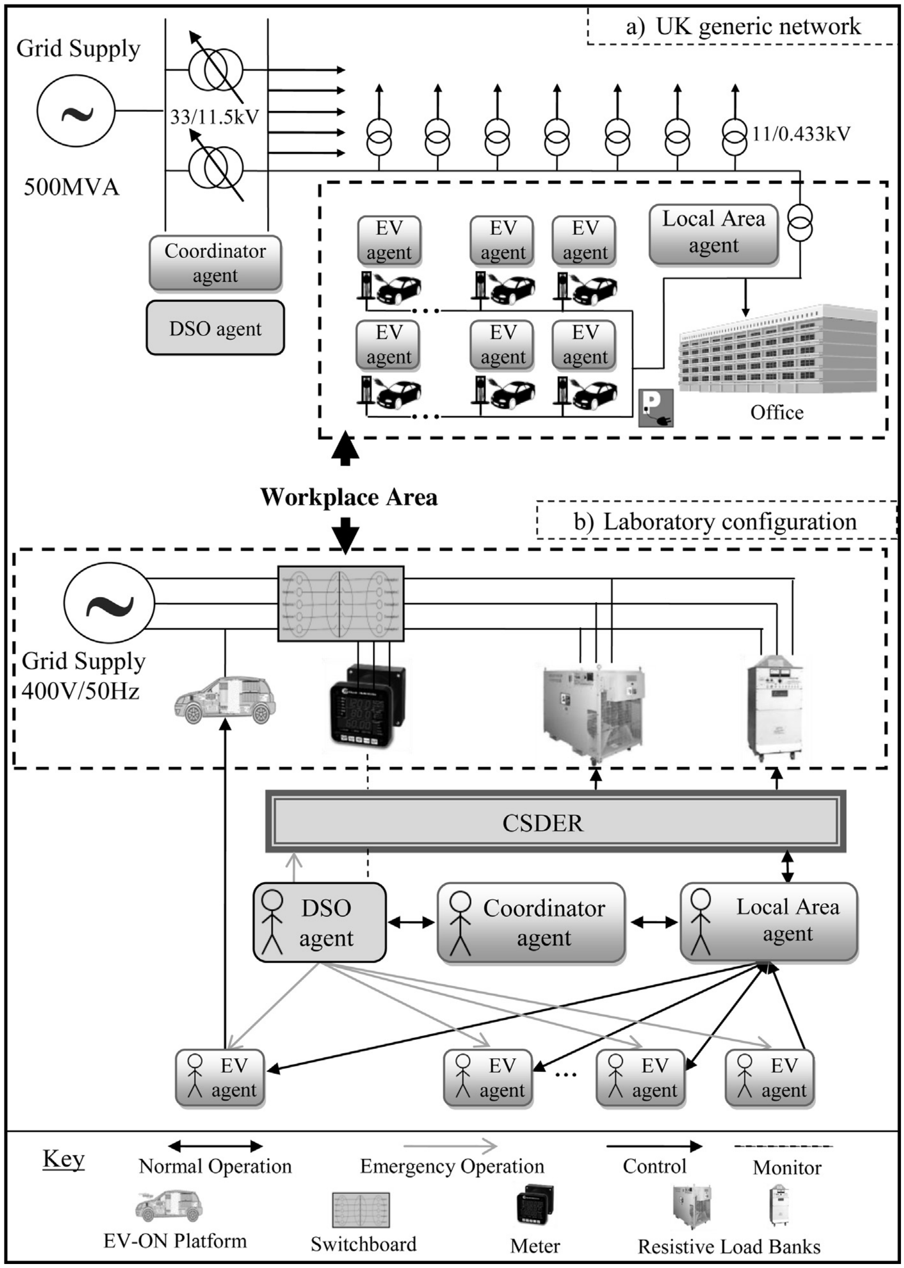


Fig. 3. Network area modelled in the laboratory.

The information sent by the coordinator agent to each local area agent is their accepted demand reduction (*Da*) for the requested hour in kW.

6. Multi-agent system evaluation

The operation of the MAS was evaluated at the laboratory of TECNALIA [19]. TECNALIA's DER micro-grid was used to configure a laboratory-scale setup of a LV area. The modelled area was the LV side of a MV/LV substation of a UK generic distribution network [20], where the residential load was replaced by a lumped load of a workplace and EV charging points, Fig. 3.

6.1. Experimental setup

The workplace and EV loading conditions were set using two controllable resistive load banks (Avtron K595 and Avtron Millennium resistive load bank). The measurements readings were obtained using the GaugeTech DMMS300 measurement acquisition device. The communication between the MAS and the laboratory resources used the Communication Services for Distributed Energy Resources (CSDER) software developed at TECNALIA [21]. The EV-ON platform [22] was used to represent an EV. The EV-ON platform developed at TECNALIA comprises a set of software and hardware resources that emulates the behaviour of an actual EV.

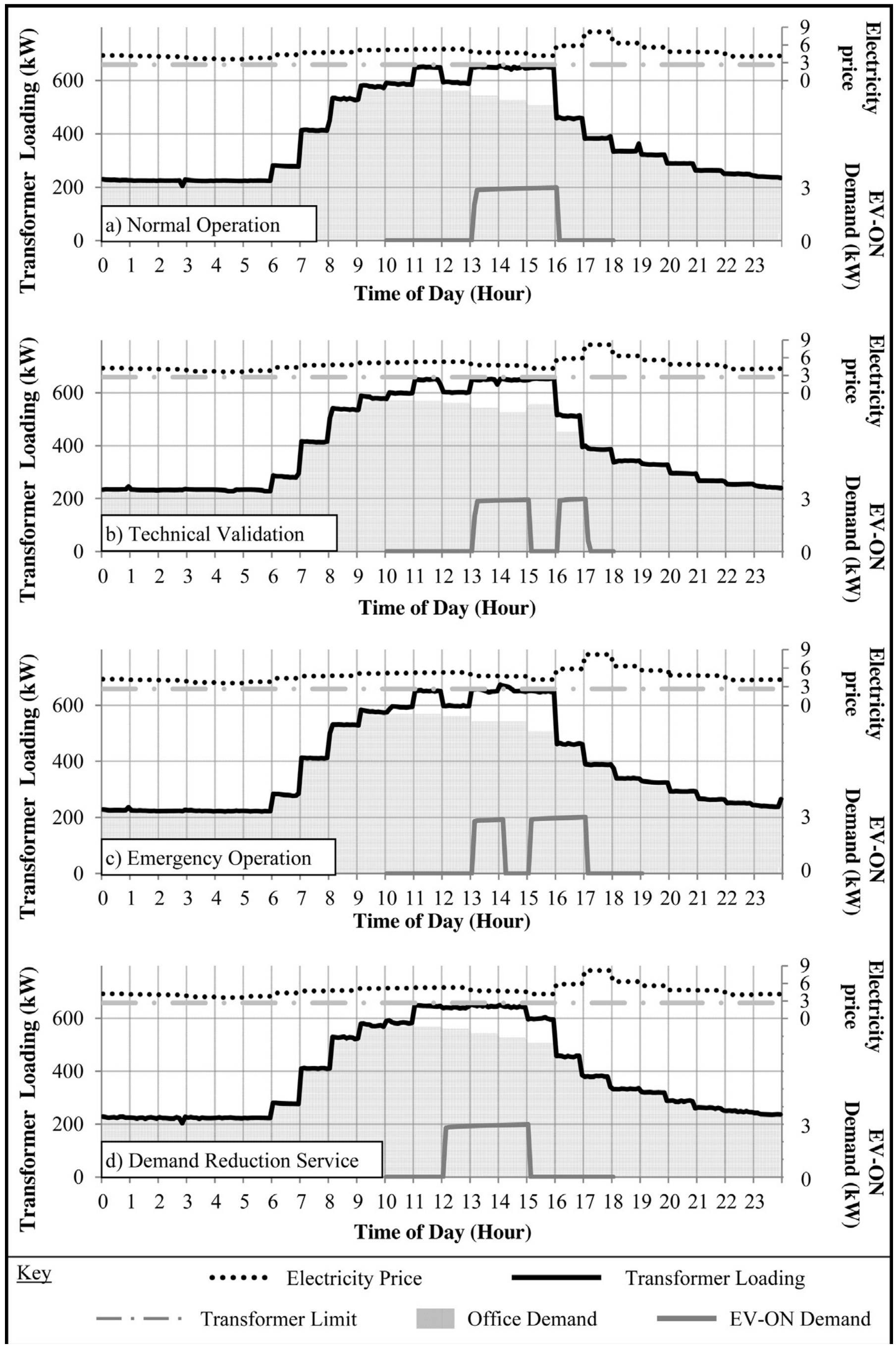


Fig. 4. Experimental results.

The multi-agent system was hosted in one computer and comprised: (i) 60 EV agents, one EV agent being adapted to the EV-ON platform software, (ii) one local area agent, (iii) one coordinator agent and (iv) one DSO agent. The Java Agent DEvelopment framework (JADE) [23] was used for the development of the MAS.

6.2. Input data and assumptions of the case studies

An office building with a charging parking facility for 60 EVs was considered. A 24 h office load profile was obtained from [24]. Each EV was assumed to have a daily energy requirement of 6.5 kWh based on [1]. EVs were assumed to be parked for 8 h; 15 EVs arriving at 8:00, 30 EVs arriving at 9:00 and 15 EVs arriving at 10:00. The on-board battery charger efficiency was 87% [2] and the battery charging efficiency was 85% [2]. EVs were charged at a constant power rate of 2.99 kW (standard charging mode: 230 V, 13 A [15]). The electricity prices used were the UK winter hourly average prices of 2010 drawn from [25]. Since the demand was aggregated at the MV/LV transformer level, the network constraint considered was the transformer loading.

6.3. Description of the case studies

6.3.1. Normal operation experiment

The aim of this experiment was to evaluate the behaviour of the Multi-agent system under normal operating conditions (i.e. no technical constraints violations) and where the EV charging set points were validated at all operational periods by the DSO agent.

6.3.2. Technical validation experiment

The aim of this experiment was to evaluate the behaviour of the multi-agent system under normal operating conditions, with the EV charging set points not being validated at a specific operational period by the DSO agent. During the technical validation of the time interval 15:00 to 16:00, the DSO agent's office forecasted demand of 15:00 to 16:00 was increased by 50 kW, emulating a short term forecasted demand increase.

6.3.3. Emergency operation experiment

The aim of this experiment was to evaluate the behaviour of the Multi-Agent System after a network constraint violation (in this case a transformer overloading).

The emergency situation was generated by modifying the workplace loading conditions through the load banks at the time interval 14:00 to 15:00, emulating an unforeseen increase of demand. Since this time interval was already close to the transformer limit, a load increase caused a transformer's limit violation. At the time interval 14:00 to 15:00 the office loading value was increased by 15 kW.

6.3.4. Demand reduction service experiment

The aim of this experiment was to evaluate the behaviour of the multi-agent system when providing active demand service in the form of demand reduction. A demand reduction was requested by the coordinator agent to the local area agent during the scheduling period of the time interval 11:00 to 12:00; the reduction was requested for the time interval 15:00 to 16:00. The targeted demand reduction at the coordinator agent was set to 50 kW.

6.4. Results of the case studies

The results are presented in Fig. 4; on the left axis the black line shows the transformer loading (EV aggregated demand plus office demand), and the grey area shows the office demand. On the right axis the black dotted line shows the electricity prices, and on the bottom right the grey line shows the EV-ON demand.

6.4.1. Normal operation experiment

The results are presented in Fig. 4(a). The total demand did not exceed the transformer loading limit. The demand was satisfied for all EVs and assigned during the cheap hours of their connection period. The simulated EV of the EV-ON platform was assigned to charge during the time intervals 13:00 to 16:00.

6.4.2. Technical validation experiment

The results are presented in Fig. 4(b). Prior to the EVs' schedules validation by the DSO, 52 EVs were scheduled to charge at time interval 15:00 to 16:00. Due to the increase in demand at this time interval, the schedules were not validated by the DSO agent and 17 EVs were re-scheduled by the local area agent to the cheapest time interval for which the EVs were still connected (16:00 to 17:00). The demand was satisfied for all EVs. The EV agent adapted to the EV-ON platform belonged to the group of EVs which demand was displaced to the time interval 16:00 to 17:00.

6.4.3. Emergency operation experiment

The results are presented in Fig. 4(c). The transformer loading limit was breached at the time interval 14:00 to 15:00, and through the curtailment of EVs the system was restored to normal operating conditions. Six EVs were curtailed and the load of the curtailed EVs was displaced to the time interval 16:00 to 17:00. The EVs curtailed belonged to the group of EVs which departure time was at 18:00 since they had the highest curtailment factors. As described in Section 4, the DSO agent curtails the EVs with the highest curtailment factors (i.e. more idle hours scheduled). The departure time of the EV agent adapted to the EV-ON platform was delayed 1 h; having the highest curtailment factor was selected to be curtailed first, as shown in Fig. 4(c).

6.4.4. Demand reduction service experiment

The results are presented in Fig. 4(d). A reduction of 50 kW was achieved at the time interval 15:00 to 16:00. Due to the demand reduction, the EV demand of 17 EVs was displaced to the time interval 12:00 to 13:00, which included the EV agent adapted to the EV-ON platform.

7. Conclusions

A multi-agent system for real-time management of EV battery charging was presented.

The operation of the multi-agent system was demonstrated experimentally through a set of experiments at TECNALIA's laboratory facilities. The purpose of the tests was to verify that the MAS was able to operate under real (laboratory) conditions, through a laboratory-scale setup, using real hardware and communications software.

Four experiments were described and demonstrated in the laboratory facilities, which showed the capabilities of the MAS to: (i) manage the EV charging schedules according to electricity prices and network constraints, (ii) adapt the charging schedules after a short term forecast load increase, (iii) reduce EV loading conditions in case of emergency situation, restoring the system to normal operation conditions and (iv) provide active demand services in the form of EV demand reduction if requested by the coordinator agent. The experiments showed the MAS capability to manage the EV battery charging avoiding overloads in the distribution network assets.

A number of issues need to be further elaborated to use this approach in anger:

(i) Integrate forecasting tools for accurate predictions on the EVs' arrival rates considering factors such as traffic flows and road congestions.
(ii) Define optimal DSO's margins of security to work within technical limits.
(iii) Add new functionalities to the MAS including additional users' requirements or dynamic prices schemes to balance its own portfolio.
(iv) Study further the optimal scheduling and operational periods' duration, considering latency in communications among agents, as well as memory and processing characteristics of the agents' hosting hardware.

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