Analysis of an Electric Vehicle Agent Based Management Model

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Abstract: An agent based control system that manages the charging of electric vehicle batteries according to distribution network constraints and electricity market price signals, is described. The system is adapted to the EV-ON platform and Microgrid equipment of Tecnalia-Lab. A case study is defined to evaluate the behaviour of the control system and the results are discussed.

I. Introduction

Uncontrolled Electric Vehicle (EV) battery charging is anticipated to modify voltage profiles of distribution feeders, overload transformers and cables, and increase power losses [1]. The Multi Agent System (MAS) technology has emerged as a potential solution to manage dispersed energy resources in distribution networks. In this research, an MAS is proposed to manage the charging of EVs. This MAS comprises a hierarchical structure based on the European Union's (EU) project Mobile Energy Resources in Grids of Electricity (MERGE) [2]. A description of the MAS and its adaptation to the EV-ON platform and Microgrid of Tecnalia-Lab is provided. A case study of the MAS operation is defined and the results are analysed.

II. Multi-agent System Description and Operation

The MAS considers two entities: (i) the EV Supplier/Aggregator (EVS/A), which facilitates the participation of the EVs into the electricity markets and (ii) the Distribution System Operator (DSO), responsible for the technical operation of the distribution system. The aggregator's hierarchy consists of: the Regional Aggregation Unit (RAU) agent, located at the primary substation; the Microgrid Aggregation Unit (MGAU) and the Clusters of Vehicle Controllers (CVC) agents, located at the secondary substation; the Vehicle Controller (VC) agent. The DSO is represented by the Central Autonomous Management Controller (CAMC) agent located at the primary substation.

The coordinator of the MAS is the RAU agent that initiates the operational period every hour. The set-points of the VC agents for the operational period are the outcome of the planning period of the previous time interval. The next planning period starts as soon as the VC agents have received the confirmation for their set-points. The MAS was designed to manage the battery charging of EVs during normal and emergency conditions. During normal operation, the EVS/A is responsible for controlling the charging of electric vehicles. During emergency mode (when transformers or cables are overloaded or voltage violates statutory) the CAMC agent can interrupt the charging of electric vehicles.

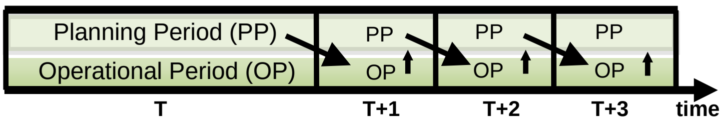

Fig. 1: Planning and operational periods of the MAS

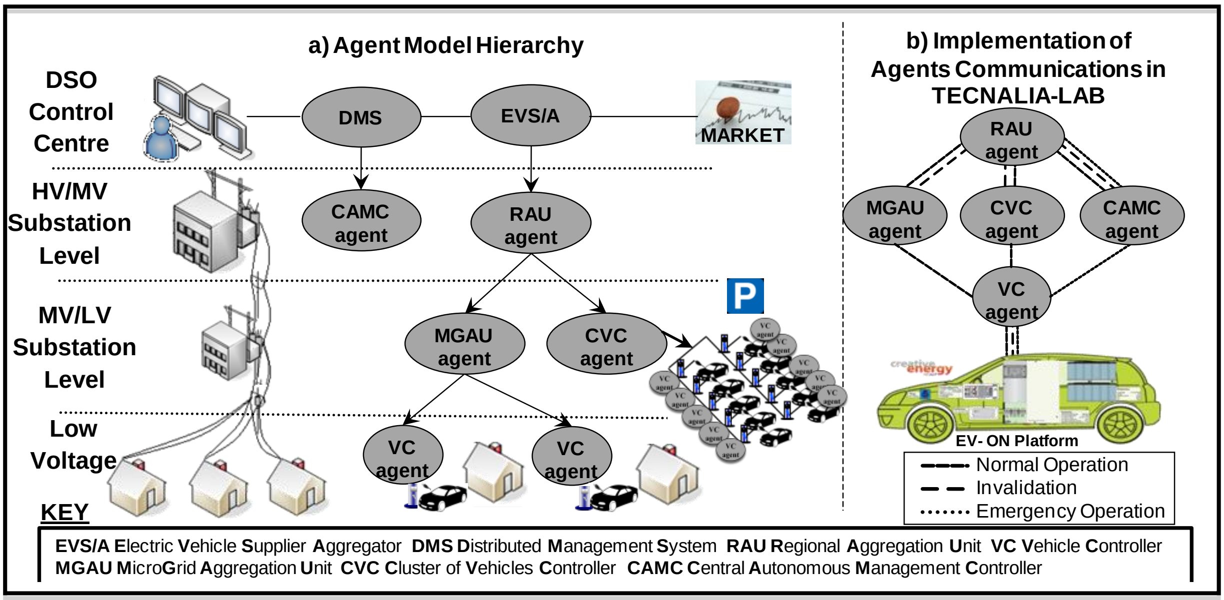

Fig. 2: Agent Model Hierarchy and EV connection with EV-ON in TECNALIA-LAB

A centralised and a distributed control of electric vehicles have been developed [3]. Fig.3 presents the information flow for the distributed control, represented by the MGAU agent, and the centralised control, represented by the CVC agent, for the normal operation mode.

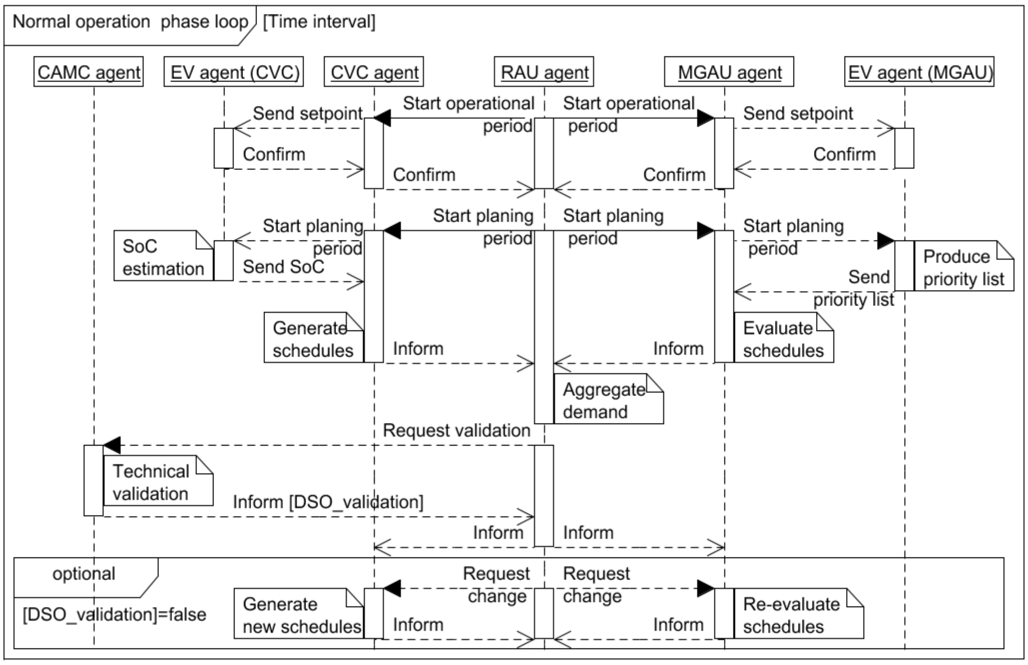

Fig. 3: Information flows and exchange of signals in the normal operation

A. Vehicle Controller (VC) Agent Description: The VC agent represents the electric vehicle owner and is designed to communicate with the MGAU, CVC and the CAMC agents. In the centralised implementation, the VC transfers (i) the actual and desired battery State of Charge (SoC) and (ii) the duration of connection, to the

MGAU / CVC agent. This agent is responsible for calculating the optimal set-points of each VC agent, based on its policy. In the distributed implementation the VC agent receives an electricity price schedule for the duration of its connection from the MGAU / CVC agent.

The VC agent produces a priority list of possible charging schedules using the resources presented in Table 1.The priority list of each VC agent contains the cost of each charging schedule and a risk factor. The schedule with the highest priority for each electric vehicle is calculated by minimising equation (1) subjected to all possible schedules. The risk factor, *R,* is calculated by equation (2).

$$\sum_{t=i}^{j} E_{Bt} p_{Bt} \tag{1}$$

Where: E_{Bt} is the amount of energy (kWh) and p_{Bt} is the energy cost at each time step *t* for the charging period *i-j*.

$$R = \frac{SoC_p - SoC_a}{e_B * e_C * P_C * H_C} \tag{2}$$

Where: SoC_p is the preferred SoC at the time of disconnection (kWh), SoC_a is the actual *SoC*, e_B is the average battery efficiency, e_C is the average charger's efficiency, P_C is the power rating of the charging point (kW) and H_C is the number of hours that the EV will be connected.

If a Vehicle to Grid (V2G) charging mode is enabled, the electricity price profile for selling electricity back to the grid is also sent to the VC agent. The schedule of the highest priority is then calculated by minimising equation (3) subjected to all possible schedules:

$$\sum_{t=i}^{j} E_{Bt} p_{Bt} - \sum_{t=m}^{n} E_{St} (p_{St} - c_{Bu}) \tag{3}$$

Where: E_{St} is the energy sold by the customer (kWh), p_{St} is the selling price of energy (£) and c_{Bu} is the battery utilisation cost (£/kWh) for the discharging period *m-n.*

The battery utilisation cost is calculated by equation (4):

$$c_{BU} = c_B * \left[\frac{(1+d)^l * d}{(1+d)^l - 1} \right] / (L * C_B * E_B) \tag{4}$$

Where: c_{Bu} is the capital cost of the battery (£), *d* is an annual interest rate, *l* the lifetime of the battery (years), *L* is the lifetime of the battery (cycles), C_B is the battery capacity (kWh) and E_B is the battery efficiency (%).

Table 1: Electric vehicle controller agent resources

VC Agent Resources	
Static Resources	*Dynamic Resources*
Inverter and Battery Efficiencies	Actual State of Charge (SoC)
Power Rating of Charging Equipment	Battery Utilisation Cost
Battery Capital Cost	Hourly Electricity Prices
Battery Nominal Capacity	Duration and Energy Required from Charging Session

At the beginning of each planning period, the process of producing the charging schedule priority list is repeated. This is to ensure that the customer preferences are satisfied in the case of: errors in SoC estimation, unforeseen charging interruptions, change of user preferences, battery self-discharge, or change in the aggregator's policy. If the customer preferences cannot be satisfied, the VC agent includes in the priority list charging schedules that do not completely satisfy the customer preferences. These profiles are prioritised based on the final SoC acquired at the end of the charging period.

B. Micro Grid Aggregation Unit (MGAU) agent and Cluster of Vehicles Controller (CVC) agent description: At each time interval, the MGAU/CVC agent receives from DSO the maximum allowable load for each network node, the EV owners' preferences and the electricity price. In the centralised control, the agent generates the optimal charging schedules. In the distributed control, the agent evaluates the charging schedules aiming to find the optimal combination based on the priority list of each VC agent. If the CAMC agent reports a technical invalidation during the planning period, the MGAU/CVC agent will generate new schedules (centralised) or re-evaluate the combination of charging profiles (distributed) accordingly, as shown in Fig.3.

C. Central Autonomous Management Controller (CAMC) Agent Description: The CAMC agent is responsible for the power delivery in distribution networks within the technical constraints. It is assumed that a real time monitoring system will be in place to provide measurements (P, Q, and V) to the CAMC agent for each network node. The CAMC agent has the following resources: (i) the topology of the distribution network, (ii) the historical load demand of each node of the network, (iii) the actual demand of each node in real time and (iv) the risk factor of each EV connected to each node of the distribution network. The CAMC agent uses load forecasts to produce a recommendation matrix with network node loading limits for the electric vehicle supply aggregator. This is done via the algorithm described in Fig. 4.

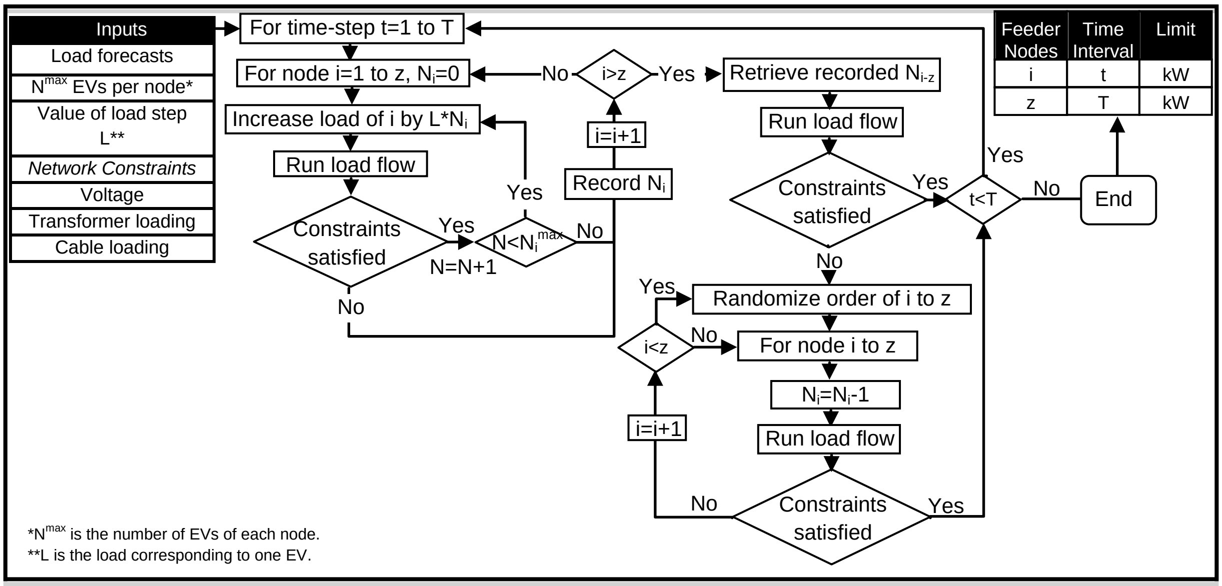

Fig. 4: Network limits matrix algorithm

The real-time role of the CAMC agent is:

i) *For Normal Operation* to validate the aggregated demand of EVs for the next operational period and to monitor the nodes of its network. The procedure of technical validation is done by means of a load flow algorithm. The CAMC agent forecasts the load demand of each node of the network during the planning period for the rest of the loads. A neural network is implemented and trained online for this load forecasting procedure. When the forecasts are obtained, the EV demand is added to each node and the load flow is executed. In the case of technical invalidation the CAMC agent updates the matrix with network constraints. In this case, the network limits are assumed final. Otherwise, the set-points for each VC agent are confirmed.

ii) *For Emergency Operation* to curtail the charging of electric vehicles in the case of severe congestion or voltage statutory limits breach. When the RAU agent requests technical validation from the CAMC agent, it sends an updated list of the EVs connected to each node. This list is prioritised according to the risk factor of the electric vehicles. If a voltage violation, branch congestion or transformer overload occurs, the CAMC agent curtails gradually the charging, starting with EVs with the lowest individual risk factor of the affected network node.

III. Case Study Description:

A case study for the year 2030 is defined. The schematic of the network used is shown in Fig. 5. The network consists of a 500 MVA three phase 33kV ideal voltage source, connected to two 33/11.5kV 15MVA transformers, an 11kV substation and six 11kV-outgoing feeders. Each feeder supplies eight 11/0.433kV transformers. From each substation, four outgoing radial feeders serve 96 single-phase customers each. The single-phase connections were distributed evenly across the three phases. The grid parameters are detailed in [4].

The model's LV side of one substation was replaced with a commercial area, assumed to supply 60 electric vehicles charging points and a lumped load of a workplace. A load profile for a workplace was scaled using data from [5]. The cable impedances of this area were neglected. The electric vehicles are managed by the CVC agent following a centralized control. For the residential area, managed by the MGAU agent following a distributed control, domestic load profiles for winter season were acquired from [5]. The EVs were assumed to be uniformly distributed across the network nodes. The assumptions for the EV uptake levels used and the characteristics of the modelled EVs are shown in Fig. 5 and Table 2.

Residential Area	
Households (Number)	384
BEVs (Number)	64
PHEVs (Number)	64
Commercial Area	
EV charging points	60
BEVs (Number)	15
PHEVs (Number)	45

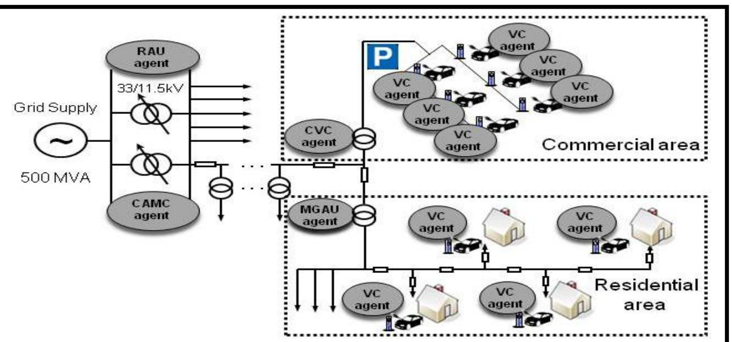

Fig. 5: Distribution network used for the study case

Table 2: Study case assumptions

BEV battery capacity (kWh)	35	*Average BEV initial State of Charge (%)*	30%
PHEV battery capacity (kWh)	9	*Average PHEV initial State of Charge (%)*	30%
EV charger rating (kW)	2.99	*EV charger average efficiency (%)*	91.7
EV battery average efficiency (%)	85	*Average EV energy requirement (kWh)*	6.5
Residential load composition: Economy/Unrestricted=16/84, Annual increase from 2003:1% [4]			

The EV batteries were modeled with Lithium charging characteristics that draw a constant current until 90% of the SoC is reached. From 90% to 100% SoC, the charging current was modeled to follow an exponential characteristic according to [6] with a maximum of 13A and a constant α of 1.026 calculated from equation (5).

$$I(t) = Imax * e^{-at} \tag{5}$$

<u>A. Test Network Configuration in Tecnalia-Lab:</u> The equipment from the microgrid facilities of Tecnalia-Lab was used to simulate part of the distribution network of Fig.5. Two load banks were used to simulate the loading of the detailed feeder of the residential area and the feeder of the commercial area (Fig. 6). A measuring device was used to provide P, Q, V values to the CAMC agent assuming that this device is connected to the LV busbar. A number of 127 VC agents were simulated for the case of the residential area and one VC agent was adapted to the EV-ON platform. A number of 59 VC agents were simulated for the case of the commercial area and one vehicle controller agent was adapted to the EV-ON platform. A load banks controller was designed to control the load bank steps in order to achieve the feeder loading for every operational period. The feeder loading was scaled to fit the equipment rating. The load banks controller and the CAMC agent used the Communication Services for Distributed Energy Resources (CSDER) software developed by Tecnalia to communicate with the equipment [7].

<u>B. Results:</u> The MAS operation was evaluated using a policy that minimises the cost of EV battery charging for each electric vehicle owner individually and for the aggregator. In Fig. 7 and 8, "feeder loading without EVs" denotes the load values given as inputs to the MAS, whereas "feeder loading with EVs" stands for the actual measurements from the laboratory. Actual measurements were below the theoretical ones due to voltage deviations from the assumed nominal voltage of 400V.

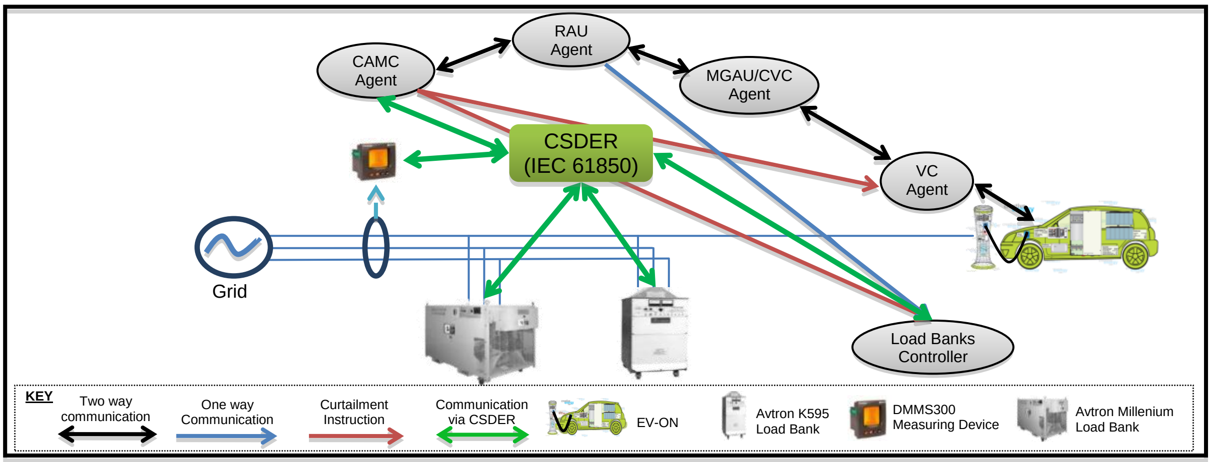

Fig. 6: Configurations used in Tecnalia-Lab

i)Residential Area: The light grey line of the primary vertical axis of Fig. 7a shows the given load of the residential feeder and the dark grey line shows the feeder load with EVs using the actual load banks and measuring device. The secondary vertical axis shows the electricity price schedule, and the power output of the EV-ON for two cases: (i) when the VC agent of the EV-ON was simulated as a PHEV with a 100% desired SoC and (ii) when the VC agent of the EV-ON was simulated as a BEV with a 50% desired SoC. The results show that the EV batteries would be charged during the cheapest hours of the day. The measurements from the EV-ON demand, when the VC agent was representing a BEV, show that the EV would charge for the three last hours of the day. When the VC agent was representing a PHEV, the EV would charge for the five last hours of the day. This is due to the 100% SoC requirement at the end of the charging session, which means that the charging current would enter the exponential characteristic during the third hour of charging. The VC agent was modeled to take this into account, allowing the EV-ON to draw a constant power. This limitation was due to the small operating range of the EV-ON battery capacity.
ii) Commercial Area: The light grey line of the primary vertical axis of Fig. 7b shows the given load of the commercial feeder. The dark grey line shows the feeder load with EVs using the actual load banks and the measuring device. The secondary vertical axis shows the electricity price schedule, and the power output of the EV-ON. In the commercial area, both BEV and PHEV batteries were assumed to charge below 90% of the SoC, thus there is no distinction in the EV-ON profiles of Fig.7b.

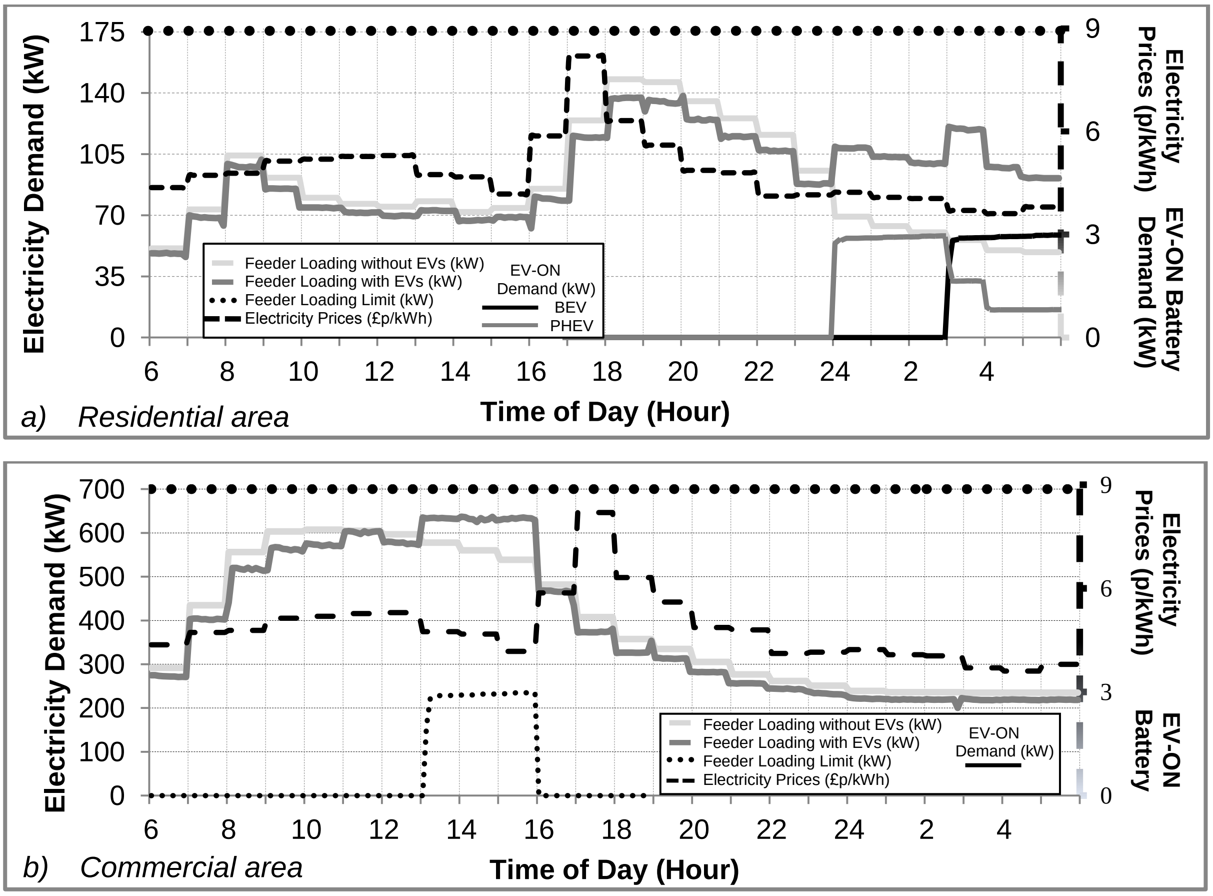

Fig. 7: Residential and commercial area results for the study case

IV. Conclusions

A Multi Agent System designed for the management of EV battery charging was described. The MAS takes into account the EV owner preferences, distribution network technical constraints and the electricity market prices. The control system was adapted to Tecnalia's EV-ON platform and used the load banks and measurement devices from Tecnalia's laboratory. The management of EV battery charging, using the proposed MAS, was evaluated in a study case. The results presented the loading conditions of a residential and a commercial area as well as charging profiles acquired from the EV-ON platform.

It was shown that the proposed agent-based system is capable of managing the EV battery charging within distribution network technical constraints, satisfying the EV load demand during the cheapest hours of the day. Further research will focus on the evaluation of the proposed MAS during an emergency, a technical invalidation from the DSO, and demand reduction services.

V. Acknowledgements

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VI. References

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