A multi-agent system for distribution grid congestion management with electric vehicles

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A B S T R A C T

Electric vehicles (EVs) are widely regarded as valuable assets in the smart grid as distributed energy resources in addition to their primary transportation function. However, connecting EVs to the distribution network and recharging the EV batteries without any control may overload the transformers and cables during peak hours when the penetration of EVs is relatively high. In this study, a two level hierarchical control method for integrating EVs into the distribution network is proposed to coordinate the self-interests and operational constraints of two actors, the EV owner and Distribution system operator (DSO), facilitated by the introduction of the fleet operator (FO) and the grid capacity market operator (CMO). Unlike the typical hierarchical control system where the upper level controller commands the low level unit to execute the actions, in this study, market based control are applied both in the upper and low level of the hierarchical system. Specifically, in the upper level of the hierarchy, distribution system operator uses market based control to coordinate the fleet operator's power schedule. In the low level of the hierarchy, the fleet operator use market based control to allocate the charging power to the individual EVs, by using market based control, the proposed method considers the flexibility of EVs through the presence of the response-weighting factor to the shadow price sent out by the FO. Furthermor, to fully demonstrate the coordination behavior of the proposed control strategy, we built a multi-agent system (MAS) that is based on the co-simulation environment of JACK, Matlab and Simulink. A use case of the MAS and the results of running the system are presented to intuitively illustrate the effectiveness of the proposed solutions.

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1. Introduction

1.1. Impact of EVs on the distribution grids

EVs are widely advocated as a mean of personal transport and urban delivery because they can contribute to the reduction of CO_2 emission, especially when the recharging electricity is generated by renewable resources. However, the electric utilities must determine how to integrate the widely distributed EVs (especially when used by a large amount of the ordinary population) smoothly into the grid, i.e., manage the simultaneous charging of a large number of EVs without overloading the grid. Typically, a charging demand of 4 kW[1] represents twice the daily demand of a normal household. Several studies (Heydt, 1983; Lopes et al., 2011; Clement-Nyns et al., 2010; Green et al., 2011) have indicated that uncontrolled charging (also known as dumb charging) of EVs will challenge the capacity of the distribution grid. To address this challenge, the time-of-use tariffs or multiple tariffs charging scheme are used in the early stage to relieve the congestions in the peak hours (Shao et al., 2010). However, using tariffs solely is not adequate to eliminate the congestion because they merely shift the peak load to its neighboring period (Ma et al., 2013; Karfopoulos and Hatziargyriou, 2013). Fortunately, there is much flexibility in terms of EV charging that can be used to mitigate the overloading problems. An example to illustrate this point is an EV charging case in the Danish power systems. In (Wu et al., 2010), a Danish driving pattern analysis was presented, which stated that the average distance in Denmark is 42.7 km per day. With an

[1] Using Nissan Leaf as an example, the typical charger for the household is 4 kW.

assumption of 0.15 kWh/km for the energy used per km of electric vehicles, one can deduce that the monthly energy requirement for an electric vehicle will be approximately 192 kWh. Using the Nissan Leaf (EV battery capacity of 24 kWh) as an example, this monthly energy requirement implied that the Leaf user must charge the EV approximately 8 times per month (192 kWh/24 kWh). However, owners will rarely fully discharge their EV before recharging it. Supposing the EV users charge the electric vehicles 20 times per month, this means 9.6 kWh of energy will be used each time. Considering the features of the charger[2], three hours are required for the charging. Normally, people leave home at approximately 7 AM in the morning and get home at approximately 5 PM in the evening, which means the EV can be charged at any three hours during the 14 h at home, in most cases.

1.2. Hierarchical control structures for EV integration management

Recently, much research has focused on the use of the EV charging flexibilities to coordinate the objectives and the constraints of the actors centrally as well as from market perspectives, e.g., to optimize the charging cost of EVs as well as to respect the hard constraints imposed by needs of the EV owner and the distribution grid operation. Regardless, in both types of coordination strategies, usually, the Fleet operator (FO) is proposed to manage the energy of EV charging as well as to provide ancillary services to the power system operator and these types of coordination forms a hierarchical control system. In addition to FO's role in this hierarchy, the role of the distribution system operator (DSO) is to operate, maintain and develop an efficient electricity distribution system. The objective of the EV owner is to minimize the charging cost given the condition that his/her driving requirements are fulfilled.

In Sundstrom and Binding (2012), a complex scheduling problem involving the EV owners, the FO and the DSO was analyzed centrally. The approach requires a complex interaction between the DSO and the FO in the upper level of the hierarchy. In each interaction, the FO will receive a specific grid constraint from the DSO and add it into the EV charging cost minimization problem in the lower level of the hierarchy. The results indicated that both the FO and the EV owners can achieve the objectives of minimizing charging costs and fulfilling driving requirements without violating the grid constraints. Lopes et al. (2009) proposed a conceptual framework consisting of both a technical grid operation strategy and a market environment to integrate EVs into the distribution systems. In that study, FOs manage the EVs, and the FOs prepare the buy/sell bids into the electricity market. Having this defined, a prior interaction with the DSO in the upper level of the hierarchical system must exist to prevent the occurrence of congestion and voltage problems in the distribution network. The smart charging algorithm was mainly designed for the operation of the DSO that can maximize the density of the EV deployment into the grid. It is also assumed that the grid has sufficient capacity to provide all of the power required by the EVs. With this assumption, the centrally smart charging approach was found to be effective. In Yao et al. (2013), the major objective of the upper-level of the hierarchy is to minimize the total cost of system operation by jointly dispatching generators and electric vehicle aggregators. The lower-level model aims at strictly following the dispatching instruction from the upper-level decision-maker by designing appropriate

charging/discharging strategies for each individual EV in a specified dispatching period. In Wang et al. (2012), the proposed hierarchical large-scale EV charging management not only meets the requirement of system dispatching but also considers the customer satisfaction.

Although these proposed solutions are demonstrated to work efficiently for a limited number of EVs, totally centralized management in a hierarchical control system requires the acquisition and processing of an enormous amount of information in the case of a large penetration of EVs, such as (1) the battery model of each EV, along with the initial state of charge (SOC) and the desired SOC of each EV battery; (2) the driving pattern of each EV; (3) the grid constraint information from the DSO; and 4) electricity market information. This enormous amount of information would require significant computational resources, communication overhead and communication infrastructure cost. Research by Lyon et al. (2012) indicated that the benefits for the entirely centralized charging management might not justify the communication infrastructure cost. Alternatively, several means of solving the congestion problem in the distribution grid have been suggested from the market perspective. The paper by Andersen et al. (2012) conceptualizes several approaches, e.g., the distribution grid capacity market and the dynamic grid tariff (O'Connell et al., 2011), to address the distribution grid congestion. The conceptualized strategies for congestion management are evaluated in terms of their complexity of implementation, the value and benefits they can offer, as well as possible drawbacks and risks. Further on, the work by Hu et al. (2014) analyzed the shadow price-based grid capacity market scheme in which the FOs centrally schedule and control the charging of EVs in the low level of the hierarchy, and they negotiate with the market operator (distribution grid capacity market) in the upper level of the hierarchy on the limited capacity of the distribution grid if it is needed. The focus of the study by Hu et al. (2014) was the mathematical proof of the proposed market scheme. Some numerical case studies were presented to illustrate the effectiveness of the proposed solution. Besides, the authors in Qi et al. (2014) presented a hierarchical optimal control framework to coordinate the charging of plug-in electric vehicles in multi-family dwellings. The charging problems of a district, e.g., an area below one primary transformer, is decomposed into several subproblems that can be solved iteratively, locally, and in parallel, with updated information of Lagrangian multipliers broadcast by the centralized controller. In general, the concept of the market based control is applied in the upper level of the hierarchy in this study to solve the congestion problem of the primary transformer. The simulation result demonstrated that the proposed hierarchical charging strategy outperforms the centralized charging strategy from the perspective of computational requirements.

1.3. Multi-agent application for EV integration management in a hierarchical structure

To implement and assess both control strategies of the smart charging of EVs, especially the market-based coordination method in a hierarchical system, a multi-agent system (MAS)-based technology is very suitable (Jennings and Bussmann, 2003), the use of which can be justified by the following reasons:

- The increase in the complexity and size of the entire EV charging network raises the need for both distributed intelligence and local solutions, which fall into the scope of MAS-based technology.
- The information flow, optimizations and the negotiations that occur in the smart charging network of EVs can be well demonstrated and integrated into a MAS.

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[2] Typically, in the European distribution network (residential area), three charging rate scenarios are considered: one-phase connections of 2.3 kW (AC 10 A $\times$ 230 V) and 3.7 kW (AC 16 A $\times$ 230 V) and three-phase connection of 6.4 kW (AC 16 A $\times$ 400 V). Using 3.7 kW as an example, this implies a charging time of approximately three hours (9.6 kWh/3.7 kW=2.6 h). Note: the DC charging method is usually used for fast charging stations.

- The system can be pre-tested and pre-analyzed by using a MAS before the actual implementation.

In addition to these general arguments, the use of a MAS has been widely proposed in the context of power systems, such as for power system restoration (Nagata and Sasaki, 2002) and for power system operation and control (Rehtanz, 2003). More recently, the multi-agent concept was proposed for distribution system operation and control (Nordman and Lehtonen, 2005; Issicaba et al., 2012; Pipattanasomporn et al., 2009; Ren et al., 2013), in particular considering the capacity management with a large population of electric vehicles (Karfopoulos and Hatziargyriou, 2013; Miranda et al., 2011) and the capacity management with more general loads (Greunsven et al., 2012). The authors (Karfopoulos and Hatziargyriou, 2013) proposed a hierarchical EV management structure in a distribution network. In the proposed hierarchical management structure, four types of agents were included in the study: EV supplier aggregator agent, regional aggregation agent, microgrid aggregation agent and cluster of vehicles controller agent, and vehicle controller agents. The authors use Nash certainty equivalence principle to formulate and solve the optimal charging problem considering the distribution network's impacts. In the non-cooperative, dynamic game, all of the vehicle controller agents decide the strategy that minimizes their own objective functions. The up-level agents (regional aggregation agent) coordinate vehicle controller agents' charging behavior by altering the price signal. The price signal is a reflection of the congestion conditions. The results indicated that the proposed approach allocates EV energy requirements efficiently during off-peak hours, which effectively achieves valley filling and also leads to maximization of the load factor and minimization of the energy losses. In this paper, the proposed hierarchical EV management structure in principle can be adapted to solve EV integration problems such as grid congestions in a big scale. However, the agents defined in the study cannot fully represent the actors in the real word, e.g., the role of the distribution system operator and the commercial actors are somehow mixed. The authors in Miranda et al. (2011) used the MAS to design a distributed, modular, coordinated and collaborative intelligent charging network, with the objective of proactively scheduling the charging of up to 50 EVs as well as eliminating the grid overloading issue. The study mainly considered how the electricity is distributed to the multiple charging point agents under one local power manager agent, which is performed by an auction mechanism. Each charging point agent makes a bid for the energy in the next 15 min until it achieves the desired state of charge of the battery, while the local power manager agent analyzes the orders to determine which EV can be charged during the time slot. The system layout of the study shows implicit relations between the local power manager agent and the national electricity system and the overall system structure is hierarchical. In the study by Greunsven et al. (2012), an active distribution network (ADN) was presented with its actors and their objectives. The multi-agent technology was proposed for the normal operation of the AND. In the proposed agent architectures, three agent named auctioneer agent (placed at the MV/LV transformer), concentrator agent installed at each feeder, and devices agents (represent DER devices) are proposed. Through this hierarchical structure, the device agents communicate with the concentrator agent to make the bids and the concentrator agent will concentrates the market bids of the connected device agents in one bid. Furthermore, the concentrator agent communicates the bid with the auctioneer agents. Then, the auctioneer agent is responsible for searching the equilibrium prices and the converged price will be sent back to the concentrator agents. The concentrator agent passes the price to all the connected device agents. By repeating the process, the system will be balanced. In addition, capacity management was investigated by transforming the bid curves of the device agents. The simulation results implemented in Matlab/Simulink demonstrated the effectiveness of the proposed agent-based solutions.

1.4. Contributions

This paper applies multi-agent technology for electric power distribution system congestion management considering the integration of electric vehicles. The unique feature of this MAS lies in its system architecture where the system is a hierarchical structure and market based control method is applied entirely in such a system, i.e., in both the upper and the lower level of the system. Thus, the proposed system exploits strengths of both market based control and hierarchical structure for application of MAS in distribution congestion management.

Furthermore, the contribution lies in the system software development where the software of JACK, MATALB, and Simulink are integrated. The built MAS fully exploits each software's strength such as JACK is a mature environment for demonstrating the coordination schemes among the multi agents, MATLAB is good for technical computation, and Simulink is good for grid modeling and simulation. Specific advantages of the current contribution over the existing work are described later in Section 6.

The remainder of this paper is organized as follows. In Section 2, the assumptions and the control system architecture used in this study are introduced. Section 3 presents the mathematical principles behind the methods of smart charging of EVs and distribution grid congestion management. In Section 4, the MAS-based realization of the congestion management scheme is presented. Case studies are illustrated in Section 5 to facilitate the understanding. Finally, discussion and conclusions are presented in Section 6.

2. Control system architecture

2.1. Main actors in the control system

Typically, the challenges in the distribution grid caused by the increasing amount of electricity consumption from EVs and heat pumps (Søndergren, 2011) are solved by expanding the grid to fit the size and the pattern of demand. As an alternative, inspired by the congestion management method at the transmission system level, in this study, the capacity of the distribution network (scarce resources) is allocated according to economic principles without upgrading the grid.

Fig. 1(a) presents a sketch of a typical situation in a distribution network, where the substation supports the electricity to the households connected to it. In this distribution network, it is assumed that the consumers own controllable appliances, i.e., EVs, in addition to some conventional loads. These EVs have contracts with the FOs, who are new entities in a smart grid environment. The use of FOs has been widely proposed to provide the charge services to EVs; here, it is further assumed that the FOs are also responsible for managing the EV charging infrastructures, i.e., the EV supply equipment (EVSE) (Bessa and Matos, 2012; San Rom´an et al., 2011). As illustrated in Fig. 1(b), the EVSE supports the smart charging functions. The decision can be made on the EV level or on the FO level. These decisions are based on the information communicated; for communication between the EVSE and the EVs, the IEC 15118 standard is the most recommended communication standard, as demonstrated in detail in Kabisch et al. (2010), Schmutzler and Wietfeld (2010), by showing the sequence diagram of a charging process between the EVSE and the EVs. For the communication between the EVSE and the FOs, IEC 61850 is recommended to fulfill the functions. We use *EVi* as an agent to represent the EV owner's operation on EVs, which will communicate with the FOs. In this study, it is assumed that the DSO will coordinate with the FOs to alter the EV's charging profile to prevent/eliminate the

Fig. 1. Illustration of the distribution network with EVs. (a) Main actors in the control systems. and (b) Relevant ICT standard between FOs and EVs.

overloading problem. The coordination between the DSO and the FOs is facilitated by the grid capacity market operator. In the following section, some market-based coordination methods will be discussed for the interaction between the DSO and the FOs.

2.2. Coordination relationships between the actors in the control system

2.2.1. Allocating the available power of DSO among the FOs by standard price-oriented market protocols

As discussed in the literature (Akkermans et al., 2004; Wellman, 1993; Cheng and Wellman, 1998), the market-based control method is very efficient and applicable for handling the resource allocation problem. The authors discussed the theoretical foundations of the distributed large-scale control problem by unifying the microeconomics and control engineering in an agent-based framework (Akkermans et al., 2004). One of the main results of this study is that computational economies with dynamic pricing mechanisms are able to handle scarce resources using adaptive control in ways that are optimal locally as well as globally. It is further recommended in the study of Akkermans et al. (2004) that the standard price-oriented market protocol, e.g., Wellman's WALRAs algorithm (Wellman, 1993; Cheng and Wellman, 1998), is suitable for implementing the agent-based microeconomic control. The algorithm presumes that an

auctioneer agent announces the market clearing price p and that the control agents will submit their demand $\gamma\alpha$ based on the price; subsequently, the auctioneer agent updates the price until the equilibrium value is found. The market-based approach has been supported to be used in the power distribution system, such as in the discussion in joint research center European Forum[3] or in the research literature (Nordentoft, 2013; Schlosser, 2010; Lorenz et al., 2009).

It should be pointed that Market based control is a paradigm for controlling complex systems with conflicting resources. It typically includes the features found in a market such as decentralized decision making and interacting agents. From control's perspective, there is a control inside this method, i.e., the upper level control uses decentralized control strategy to control the low level units. From market's perspective, there is also a market inside this method, i.e., the upper level controller negotiate with the low level units to reach an agreement, for example, in this study, the distribution system operator and the fleet operators are negotiating the transformer capacities that is facilitated by the grid capacity market operator.

2.2.2. Coordination method between FOs and EV owners

The control method between the FO and the EVs developed in (Sundstrom and Binding, 2012; Lopes et al., 2009; Hu et al., 2014) follows the centralized control strategy, while the one developed in Ma et al., (2013), Karfopoulos and Hatziargyriou (2013) follows the decentralized control strategy. The studies of Karfopoulos and Hatziargyriou (2013) and Richardson et al. (2012) compared the centralized control and decentralized control method when utilizing them to make an optimal plan that can optimally deliver energy to EVs as well as avoid grid congestion. These studies outlined the advantages and disadvantages of both strategies. In this study, the market based control method is used by the FO to coordinate the EVs' charging schedule.

2.3. Integrated two-level hierarchical control method for distribution grid congestion management with EV integration

Shadow price protocols are proposed for the coordination between the DSO and the FOs agent in Hu et al. (2014) in which the shadow price used as a market clearing price is updated in each bidding round by the grid capacity market operator (serving the DSO). The bids are coming from the FOs that represent the EVs and directly schedule and control the charging of EVs. In this study, we modify the coordination method between the FOs and the EVs by distributing the charging decision to the EV agent. A response weighting factor to the shadow price is introduced to the individual EV agent. In this manner, the EV agent can show their willingness to charge or not during the higher price time slot.

In the following section, a detailed logic of the two-level hierarchical coordination is proposed for integrating the EVs into the power distribution systems. Fig. 2 shows the steps of the proposed methods:

1. The EV owner selects the desired charging requirements, and the EV controller generates the charging schedule based on, e.g., the charging least cost strategy, the dumb charging strategy, etc.
2. The EV owner sends the charging schedule to the FO to which they have been subscribed.
3. The FOs aggregate the charging schedule from their contracted EV owners and submit the aggregated charging schedule to the DSO.
4. The DSO verifies the charging schedule of the FOs by running load flow calculation and sends the results to all of the FOs.

5. The FOs submit the charging schedule to the market operator if congestion exists; otherwise, the FOs could bid the energy schedule to the energy spot market and the procedure stops in this step.
6. The Market operator sends the shadow price to the FOs, and then the FOs re-submit the charging schedule to the Market operator until the shadow price is converged.
7. The FOs send the shadow price to all of the EV controllers.
8. Repeat steps 1 to step 7 until the congestion is totally eliminated in the planning period.
9. Bid the final energy/power schedule to the electricity spot market.

The key concept is that the energy schedules of the FOs/EVs are coordinated by the DSO/Market operator before they are sent to the energy market.

2.4. Further discussion on the proposed method

With the purpose of further illustrating the proposed distribution grid capacity market, we provide a basic introduction to the congestion management method and the markets, i.e., Spot market and Regulating power market, operated at the transmission system level. Three very different methods of managing the congestion of the transmission system in the deregulated environment were presented by Christie et al. (2000). The three methods are the optimal power flow model used in the United Kingdom, Australia, New Zealand, and some parts of the United States; the price area based model used in the NordPool market area in Nordic countries; and the transaction-based model used in the United States. In the Spot market, the Power Balance Responsible parties (PBRs) make the power and energy bids into the market, which consists of conventional power and wind power. With the trading, the PBRs can balance the power systems in the deregulated environment. Because electricity production and consumption always have to be in equilibrium, deviations in the operating hours are left for the transmission system operator (TSO) to balance, which is achieved via the regulating power market. Note that the dispatch currently is set based only on the spot market, without consideration of the operational state of the distribution grid. Briefly, the proposed solution of this study can enable the distribution congestion management before the operation of the dispatch. Additionally, the capacity market we proposed only
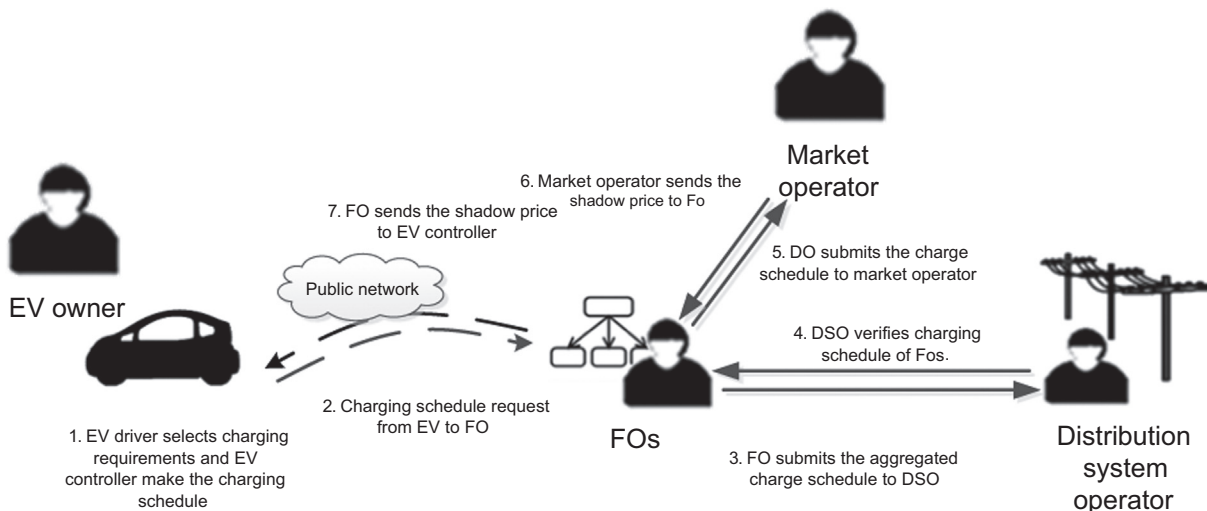

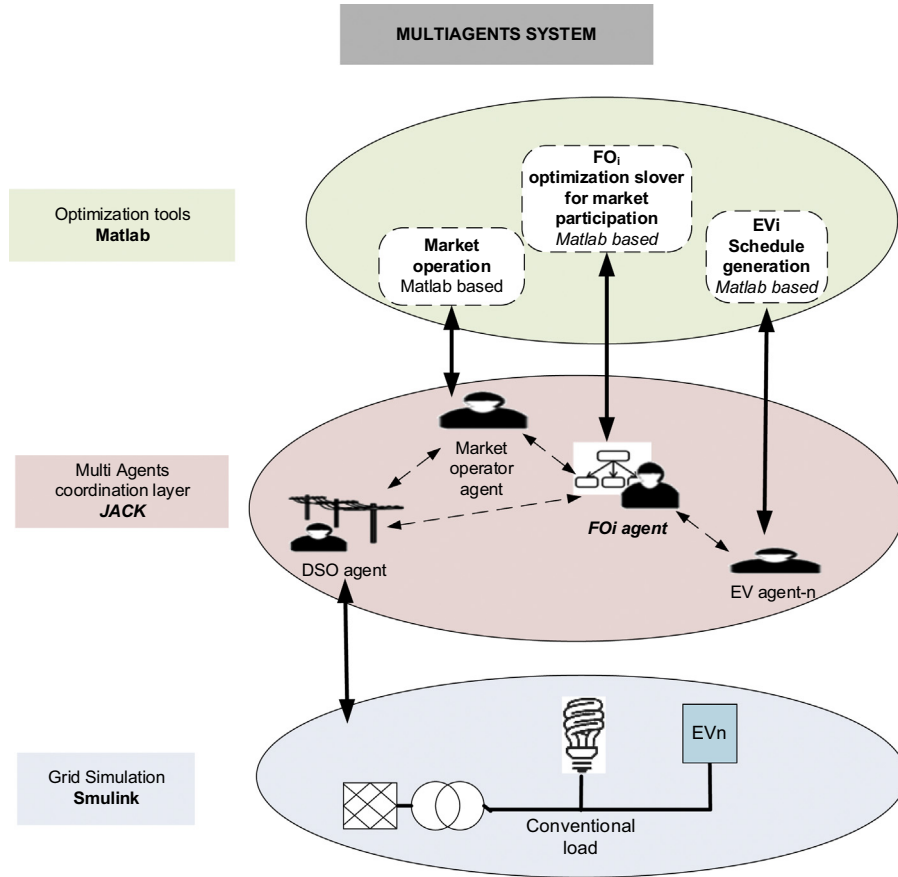**Fig. 2.** Scheme of the proposed solutions.

Fig. 3. Multi-agent system architecture.

occurs when it is required, i.e., in the situation of possible congestion predicted by the DSO.

In addition, we assumed that FOs fully cooperate in the grid capacity market to avoid the congestion issue. This assumption is made based on the previous discussion (McCalley et al., 2003; Raiffa, 1982) in which three types of negotiations were characterized as either strident antagonist, cooperative antagonist, or fully cooperative. The strident antagonist negotiation involves agents that completely distrust each other. The cooperative antagonist negotiation involves agents that are entirely self-interested but are ones that recognize and abide by whatever rules exist. The fully cooperative negotiation involves agents that do not perform strategic posturing and consider themselves as a cohesive entity, with the intention to arrive at the best decision for the entity, although they have different needs, values, etc. By being fully cooperative in our context, FOs will honestly submit the bids based on their marginal cost functions, and the impartial market operator will update the market clearing price only reflecting the constrained resources (distribution grid capacity).
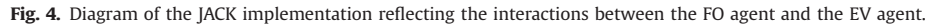
Finally, in this shadow price mechanism-based method, the EV owner needs to pay the higher shadow price if they charge the batteries of the EVs in the time slot where congestion occurs and the DSO seems cost nothing when seeking to eliminate the grid congestion. However, in actual practice, it is the DSO's responsibility to upgrade the network to address the challenges. It is therefore assumed that the shadow price can be modified when it is sent to the FOs or the FOs may receive compensation from the DSO. In addition, the DSO must support the operation of the market operator and can investigate means of reducing cost based on the implementation of information and communication infrastructures in the distribution grid.

3. Problem formulation and development of the control algorithms for EV charging schedule generation and grid congestion management

In this section, we first introduce the newly defined method for the EV charging schedule generation and then summarize the key elements of the mathematical formula development of our previous work (Hu et al., 2014), i.e., the algorithm for shadow price-based coordination.

3.1. EV charging schedule generation

Linear programming is used and modified to model the charging process of EVs (Hu et al., 2014, 2011). The objective is to minimize the charging cost as well as to fulfill the driving requirement of the EV owner. The scheduling period is divided into N_T time slots, where each time slot could be hourly based or fifteen/ten minutes depending on the modeling requirements. The objective function is defined as the product of the virtual price (predicted electricity price and the weighted shadow price in which the shadow price reflects the congestion cost of the distribution grid) and a decision variable $P_{j,i}$, where $j = 1, 2, ..., N_E$ is the index for the number of EVs under one FO, and N_E denotes the number of EVs under FO k. $i = 1, 2, ..., N_T$ is the index for the time slot in the scheduling period. The physical meaning of the decision variable $P_{j,i}$ is to make a decision to distribute/charge the power on the certain time slots, with the goal of minimizing the charging cost. The predicted electricity price is assumed to be known in each time slot. With the defined objective function and the constraints of (1) the available energy in the battery should be greater than or equal to the energy requirement for the

Fig. 4. Diagram of the JACK implementation reflecting the interactions between the FO agent and the EV agent.

next trip/time slot, (2) the available energy in the battery should be less than or equal to the power capacity of the battery, and (3) the charging rate should be less than or equal to its maximum power rate of the charger, the mathematical model of the solution is presented as follows:

$$\text{Minimize} \quad \sum_{i=1}^{N_T} \left(\Phi_{j,i} + \varepsilon_i * \Lambda(i) \right) P_{j,i} t, \quad = 1, \ldots, N_k^E$$

Subject to

$$
\begin{cases}
SOC_{0,j} + \sum_{i=1}^{N_T} P_{j,i} t_{j,i} \geq SOC_{Min,j} + \sum_{i=0}^{N_{T-1}} E_{drive,i+1} \\
SOC_{0,j} + \sum_{i=1}^{N_T} P_{j,i} t_{j,i} \leq \omega * E_{cap,j} + \sum_{i=2}^{N_{T+1}} E_{drive,i-1} \\
0 \leq P_{j,i} t_{j,i} \leq E_{\max\ j}, \quad i = 1, \ldots, N_T
\end{cases}
\tag{1}
$$

where $\Phi_{j,i}$ denotes the predicted day-ahead electricity market price vector, $\Lambda(i)$ represents the shadow price, ε_i denotes the responding weighting factor of the shadow price, and t denotes the length of each time slot. $SOC_{0,j}$ denotes the initial SOC of an individual EV battery. $SOC_{Min,j}$ denotes the recommended minimum SOC of the EV battery. E_{drive} denotes the predicted individual EV owner's driving requirement. $E_{\max\ j}$ denotes the charge rate in terms of the energy of an individual EV battery. $\omega * E_{cap,j}$ denotes the recommended maximum SOC of the EV, where ω is the parameter that indicates that the charging behavior of the battery of the EV is a linear process, and $E_{cap,j}$ is the capacity of the battery of the EV.

With the above optimization problem, each EV agent can generate a unique energy schedule; the sum of the individual EV energy schedules in one FO will be denoted as $P_{k,i}^E$ and

$$P_{k,i}^E = \sum_{j=1}^{N_k^E} P_{j,i}, \quad k = 1, \ldots, N_B, \quad i = 1, \ldots, N_T$$

where N_B represents the number of the FOs, and k denotes the index for the number of FOs, $k = 1, \ldots, N_B$. This scheduling is the key computation method that is used in this study for step 1, which is described in Section 2.3. In steps 2 and 3, there are no issues that must be clarified. In step 4, the distribution system operator previews and analyzes the distribution network by running the load flow calculation in Simulink, where a 10-kV distribution network is modeled. The math behind steps 5, 6, and 7 will be explained in the following subsection.

3.2. Market based control for distribution grid congestion management

To describe the market based control method, we start with a proposed cost function, which represents the cost of the power preference difference of an FO in each time slot, e.g.,

$$\mu_k = C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2 \tag{2}$$

where i, k, $P_{k,i}$ remain the same with the above notation, $\tilde{P}_{k,i}$ denotes the control variable, and $C_{k,i}$ denotes the weighting factor that is associated with the power difference; a larger value of $C_{k,i}$ implies a smaller difference. The objective is to minimize the cost functions of all of the FOs as well as to address the constraint from the DSO:

$$\text{minimize} \quad \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i} \left(\tilde{P}_{k,i} - P_{k,i}^E \right)^2$$
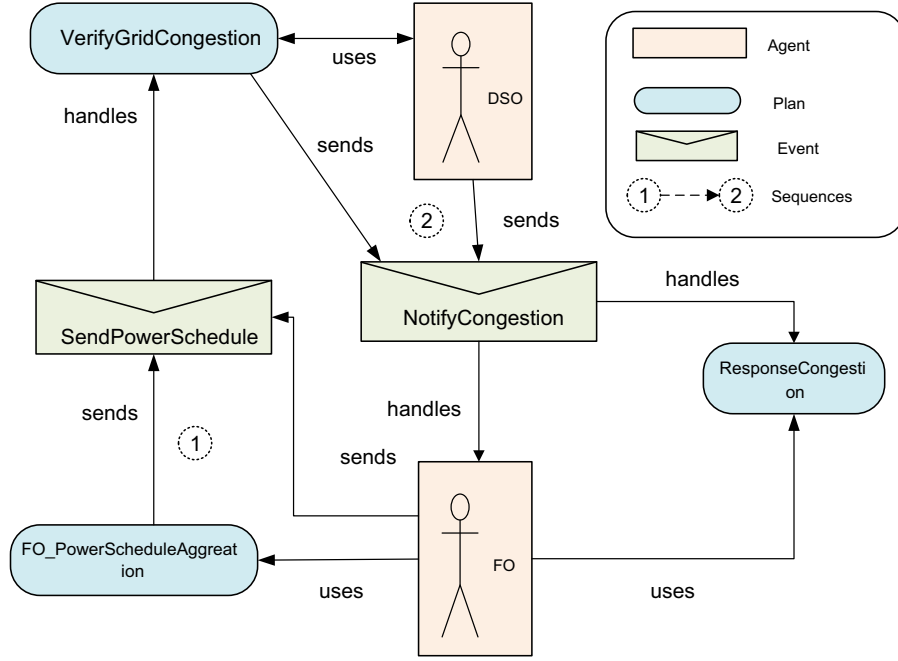
Fig. 5. Diagram of the JACK implementation reflecting the interactions between the FO agent and the DSO agent.

subject to

$$\sum_{k=1}^{N_B} \tilde{P}_{k,i} \le P_{Cap}(i), \; i = 1, ..., N_T, \tag{3}$$

where $P_{Cap}(i)$ is the power capacity specifically for all of the FOs, for example, it can be estimated by the DSO after deducting the conventional loads. This problem is a convex optimization problem, and relevant research (Boyd and Vandenberghe, 2004; Boyd et al., 2007) indicates that by introducing Lagrange multipliers or shadow price $\Lambda(i)$, problem (3) can be transferred into the following partial Lagrangian problem:

$$L = \sum_{k=1}^{N_B} \sum_{i=1}^{N_T} C_{k,i}\left(\tilde{P}_{k,i} - P_{k,i}^E\right)^2 + \sum_{i=1}^{N_T} \Lambda(i)\left(\sum_{k=1}^{N_B} \tilde{P}_{k,i} - P_{Cap}(i)\right) \tag{4}$$

The centralized optimization problem (3) is transferred into a decentralized one with an associated shadow price $\Lambda(i)$ in each time slot, with the purpose of emulating the market behavior. In the starting point, the shadow price is assumed to be zero, and then the optimal solution for Eq. (4) is $P_{k,i}^E$. As a result, in step 5, the FOs first directly submit their power schedule to the market operator and the market operator will determine the shadow price. Because the market operator's interest is in alliance with the DSO, i.e., eliminating the grid congestion, as further explained in the studies by Hu et al. (2014) and Boyd et al. (2003), the shadow price can be updated according to $\Lambda(i)^{\omega+1} = \Lambda(i)^{\omega} + \alpha_{\omega}.(\Sigma_{k=1}^{N_B} P_{k,i}^*(\Lambda^*) - P_{Cap}(i))$ until the price converges, where $P_{k,i}^*(\Lambda^*)$ is the optimal solution of Eq. (4) with the given Λ^*, i.e., the newly $\Lambda(i)^{\omega+1}$, where ω is the number of convergence steps required, $\alpha_{\omega} \in R$ denotes the step size and can be chosen as $\alpha_{\omega} = \alpha$, which is a positive constant; with such a choice, the convergence is guaranteed. This process represents step 6.

In step 7, the FO sends the shadow price to all of the EV controllers. Then, each EV controller restarts at step 1; the only difference is that a shadow price is added on the top of the predicted spot energy prices, and the modification compared to the study by Hu et al. (2014) lies in the response weighting factor γ to the shadow price. The EV owners can show their will by assigning the appropriate values to the response weighting factors. For example, if γ is zero, it represents that the EV owner is fully

insensitive to the shadow price and will keep the original power schedule; otherwise, a new power schedule will be generated and submitted to the FOs. By repeating the steps, the proposed solution can ensure the safety of the grid in the planning period.

4. Multi-agent model for control system demonstration

To demonstrate the operation of the control systems, a multi-agent system is developed and built in this study. In this section, first, the multi-agent system architecture is described. Next, we briefly introduce the features of the JACK software. Finally, we present the use case and its multi-agent system implementation.

4.1. Multi-agent system architecture

Fig. 3 depicts the MAS system architecture in which all of the agents are built in JACK, which is an agent-oriented development environment built on top of and fully integrated with the Java programming language (Howden et al., 2001). JACK offers the environment and facilities message sending/receiving between the agents. Matlab-based functions enable a declarative implementation of the decision module that supports the operations of the agents built in JACK. Simulink is used to model the distribution grid and functions for the power flow calculation that supports the operation of the DSO agent. The Java application programming interface matlabcontrol[4] is used for JACK to interact with Matlab. Through this interface, the agents in the JACK can access the functions, e.g., built in the Matlab.

4.2. Introduction on the features of JACK

The agents used in JACK are modeled according to the theoretical Belief Desire Intention (BDI) model of artificial intelligence (Wooldridge, 2008). Within the environment, a JACK agent is a software component that can exhibit reasoning behavior under

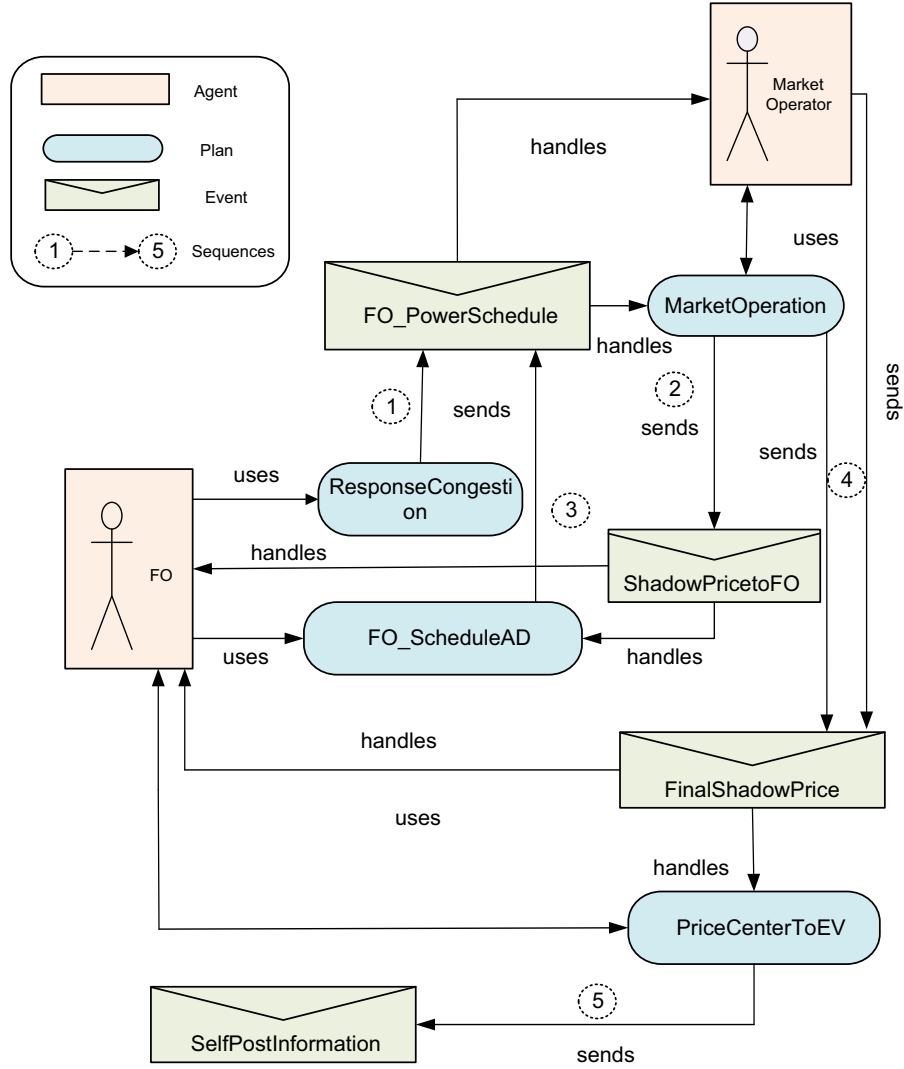---

[4] https://code.google.com/p/matlabcontrol/.

Fig. 6. Diagram of the JACK implementation reflecting the interactions between the FO agent and the market operator agent.

both proactive (goal directed) and reactive (event driven) stimuli. As key components of JACK, the JACK agent language introduces five main class-level constructs:

- Agent: models the main reasoning entities in JACK.
- Event: models the occurrences and messages to which these agents must be able to respond.
- Plan: models procedural descriptions of what an agent does to handle a given event; an agent's plans are analogous to functions.
- Capability: aggregates the functional components (events, plans, belief sets, and other capabilities) for agents to use.
- Belief set: models an agent's knowledge about the world.

In this study, we mainly use the three class levels: the agent class, the event class, and the plan class.

4.3. Use case and the MAS implementation

4.3.1. Agent class and its instantiation

In our use case described in chapter 2, four types of actors exist in the control systems, where the roles of the actors and the coordination relationships between the actors have been clearly addressed. Because one of the important features of the multi-agents system is to model the capabilities of agents and their interactions, it is therefore decided that four types of agents are designed for the system's MAS implementation, i.e., EV agent, FO agent, DSO agent and Market operator agent. Each agent's role is briefly introduced in the following section. Considering the features of JACK and the requirements of our desired systems, we use the agent class in the design views that make the instantiation of an agent flexible. In addition, each agent has several plans that are used to handle the events.

- EV agent: An EV agent class is responsible for generating the charging schedule of the individual EVs. They communicate with the subscribed FOs.
- FO agent: An FO agent class is responsible for aggregating the charging schedule of their contracted EV agents and modifying the power schedule when negotiating with the market operator agent. The FO agent communicates with EV agents, the DSO agent, and the market operator agent.
- DSO agent: A DSO agent is responsible for the grid safety by performing a load flow calculation after obtaining the power schedules of the FOs. The DSO agent communicates with the FO agents and the market operator agent.
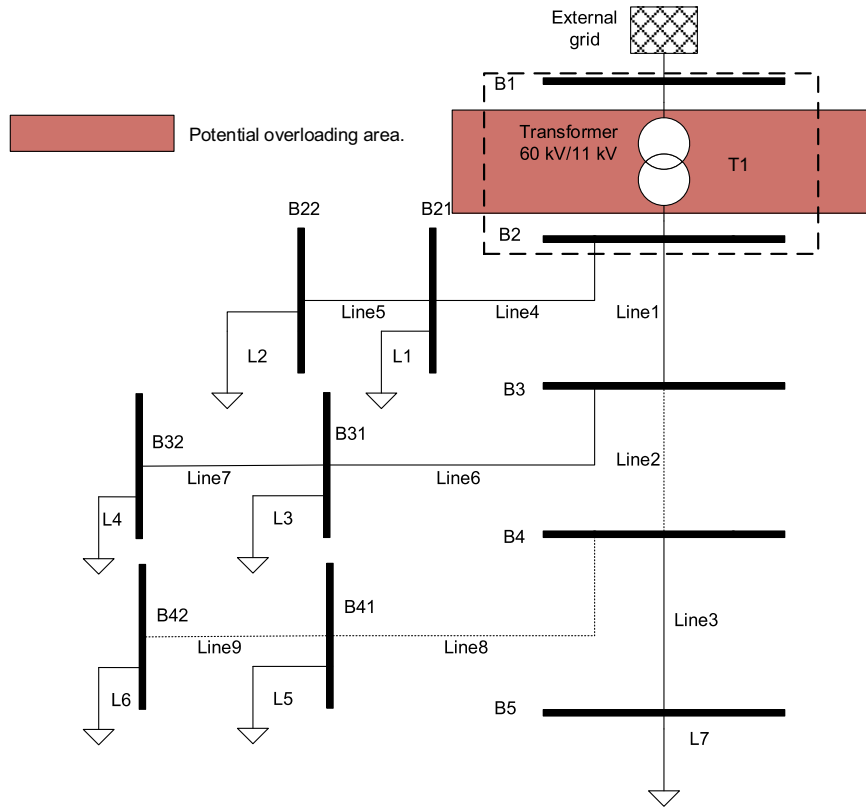
Fig. 7. A 10 kV distribution network.

- Market operator agent: A market operator agent is responsible for setting the shadow price. The market operator agent communicates with the DSO agent and the FO agent.

4.3.2. Multiagents built on JACK

The entire design diagram for the desired multi-agent systems based on JACK has been built according to the proposed solutions in this study, i.e., the eight steps presented in Section 2.3. To present the implementations in detail, we will explain this diagram according to the sequence of the steps and logically divide it into three parts. The three parts are named as (1) interaction between the FO agents and the EV agents, (2) interaction between the FO agents and the DSO agent, and (3) interaction between the FO agents and the market operator agent.

4.3.3. The interaction between the FO agent and the EV agent

In the implementation, the FO provides the calculation center to the EV agents to facilitate the computation, although it is assumed that the EV agent sets the charging schedule by himself/herself. With this implementation, the programming time can be significantly reduced.

As illustrated in Fig. 4, each EV agent first posts an Event named SelfPostInformation to trigger the plan EVSelfInformation. With this plan, the EV agent reads the information, including the initial SOC, the driving requirement of the EVs in the scheduling period, the bus information[5] and the response weighting factor to the shadow price. After obtaining the personal information, the EV agent sends an event named AskingPowerCalculation to the FO agent, and the event will be handled by the plan FO_CalculationCenter. In the plan, a

Matlab-based program will be called and used to generate the charging power schedule. The power schedule will be sent back again to the EV agent by the event ChargingSchedule. The Event is handled by the plan named EV_ChargingSchedulePreparing. With the plan, the EV agent sends the power schedule and the corresponding bus information to the FO agent by the event named EV_SendChargingSchedule; this event will be handled by the plan FO_PowerScheduleAggregation. Using this plan, all of the contracted EV's power schedule will be summed according to which bus they are connected.

4.3.4. The interaction between the FO agent and the DSO agent

In this diagram (Fig. 5), each FO agent sends the aggregated power schedule to the DSO agent by the event named SendPowerSchedule. The event will be handled by the DSO agent with the plan VerifyGridCongestion. With this plan, the DSO agent will call the grid model built in Simulink with the newly developed power schedule of the FOs and the conventional loads and perform the power flow calculation. The DSO agent can fetch the value from Simulink and compare it with the capacity of the distribution grid, such as the transformers. Then, the DSO agent will send the result to all of the FO agents through the event named NotifyCongestion. The event will be handled by the plan ReponseCongestion. With the plan ReponseCongestion, all of the FO agents obtain the result and check whether congestion exists. If it is congested, all of the FO agents will resort to the market operator agent to negotiate the power capacity. Otherwise, the FO agents are allowed to bid the energy schedule into the energy spot market.

4.3.5. The interaction between the FO agent and the market operator agent

In the interaction illustrated in Fig. 6, the FO agent sends the power schedule to the market operator agent by the event

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[5] Buses of the modeled distribution system are implemented in Simulink in which several load buses are defined for connecting the EVs.
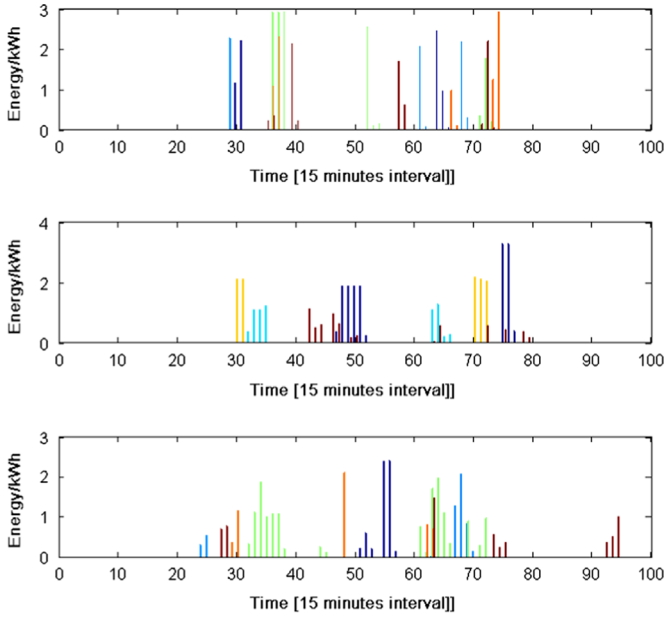
Fig. 8. EV energy driving requirement per EV agent per FO.

FO_PowerSchedule, and the event will be handled by the market operator agent with the plan MarketOperation. Within the plan, the market operator agent calls the Matlab-based price determination program and determines whether the price is converged in each iteration loop. If the price is not converged, the market operator agent will send the updated shadow price to the FO agent by the event ShadowPricetoFO. Accordingly, this event will be handled by the agent with the plan FO_ScheduleAD. Within this plan, the FO agent will reschedule the power based on the predefined cost functions and the updated shadow price and resend the power schedule to the market operator agent by the event named FO_PowerSchedule. If the price is converged, the market operator agent will send the final shadow price to the FO agent by the event FinalShadowPrice. The event will be handled by the FO agent with the plan PriceCenterToEV. In this plan, the FO agent does not send the shadow price to the EV agent directly because the calculation center is placed on the FO agent level. Instead, the FO agent sends a normal message through the event SelfPostInformation to simulate the entire interactions between the agents again.

Note that when the price is converged, a complete sequence of the operation required for grid congestion has been performed. However, the newly acceptable power schedule of the FOs might deviate from the original plan. Therefore, we provide an opportunity for the FOs and the EV owners to make a new schedule based on the information of the first round. This is why the final shadow price is sent to the FO agent by using the event FinalShadowPrice. To run the complete sequence again, the EV agents require a signal to stimulate the corresponding plans; this signal is stimulated by the event SelfPostInformation sent out by the market operator agent using the plan PriceCenterToEV.

5. Simulation and demonstration results

5.1. Case study specification

A 10 kV radial network is considered in this case study; the one-line diagram/topology of the network is shown in Fig. 7. The network is modified from Østergaard and Nielsen (2008) and Han (2012), which can represent the typical features of a Danish

distribution system. The network consists of two voltage levels, 11 buses, 9 distribution lines, and 7 load buses; the network is modeled in Simulink. A total of 1400 households are connected in this distribution system, and 20% of the households are assumed to have EVs. Considering the similarities of the driving patterns of the EV users and the simulation requirements of the multi-agent systems, we divide the 280 EVs into 14 groups, which are represented by 14 EV agents. Three FOs are assumed to provide services to these 14 EV agents. FO1 is responsible for EV agents EV1 to EV5. EV6 to EV9 are assigned to FO2. The remaining EV agents subscribe to FO3. If all of the EVs are connected to the grid at the same time, this will bring an additional load of 644 kW to the network the maximum individual EV charging rate is limited to 2.3 kW, which corresponds to the Danish case (10 A, 230 V connection). In our case study, the available power capacity for all of the EVs is 600 kW (available capacity of the primary transformer for EVs). The weighting factor rate $C_{1,i}$, $C_{2,i}$, $C_{3,i}$ is set to 0.5, 0.1, and 0.2, respectively. The value of α_ω is chosen as 0.1 in this case.

For the EV charging schedule, the information of the hourly electricity spot price of the Nordic power market[6] is assumed to be perfectly known by the EVs, and the price data are identical with the data of a previous study (Hu et al., 2014). The artificial driving data of the 14 EV agents were generated based on the 2003 AKTA Survey (Christensen, 2011) in which 360 cars in Copenhagen were tracked using GPS from 14 to 100 days. Each data file includes a starting and finishing time, and the corresponding duration and distance. The original data are transferred into 15-minute interval driving energy requirements based on the assumption of 11 kWh/100 km. The 15-minute interval is changeable rather than absolute. The energy driving requirement of EV1 to EV14 is illustrated in Fig. 8. Most EVs are observed to exhibit a regular pattern, i.e., they leave home in the morning time and come back in the evening time, while some EVs have higher energy driving requirements, such as EV agent EV13, which is shown by the green curve of the bottom figure. For the other parameters:

- The battery capacity of each of the EV agents is set to 20 kWh.
- The initial SOC of each of the EV agents is set to 0.2 of the battery capacity.
- The minimum SOC of each of the EV agents is set to 0.2 of the battery capacity.
- The maximum SOC of each of the EV agents is set to 0.85 of the battery capacity, and the minimum and maximum SOC set up is to ensure that the EV charging process is linear.
- The responding weighting factors to the shadow price of the EV agents are assumed to be (0.01, 0.01, 0.01, 0, 0, 0.01, 0.01, 0, 0, 0.01, 0.01, 0.01, 0, and 0), correspondingly.

5.2. Simulation results in MATLAB

In this simulation section, we compared the result of two cases where the DSOs both use the price-oriented market protocols to interact with the FOs; however, the coordination methods between the FOs and the EVs are different. In the first case, we assume that three FOs centrally schedule and control the EV charging, which is the scenario described in the previous work (Hu et al., 2014), while in the second case, it is assumed that three FOs only aggregate the charging schedules that are made by the EV controllers, which is the scenario in this study. As illustrated in Fig. 9, the congestion problems are solved after 5 steps in the first case, while only 2 steps are required in the second case. The reason for this difference is described as follows. The EVs in the first case are always responding to the shadow price

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[6] http://www.nordpoolspot.com/.

a

b

c

d
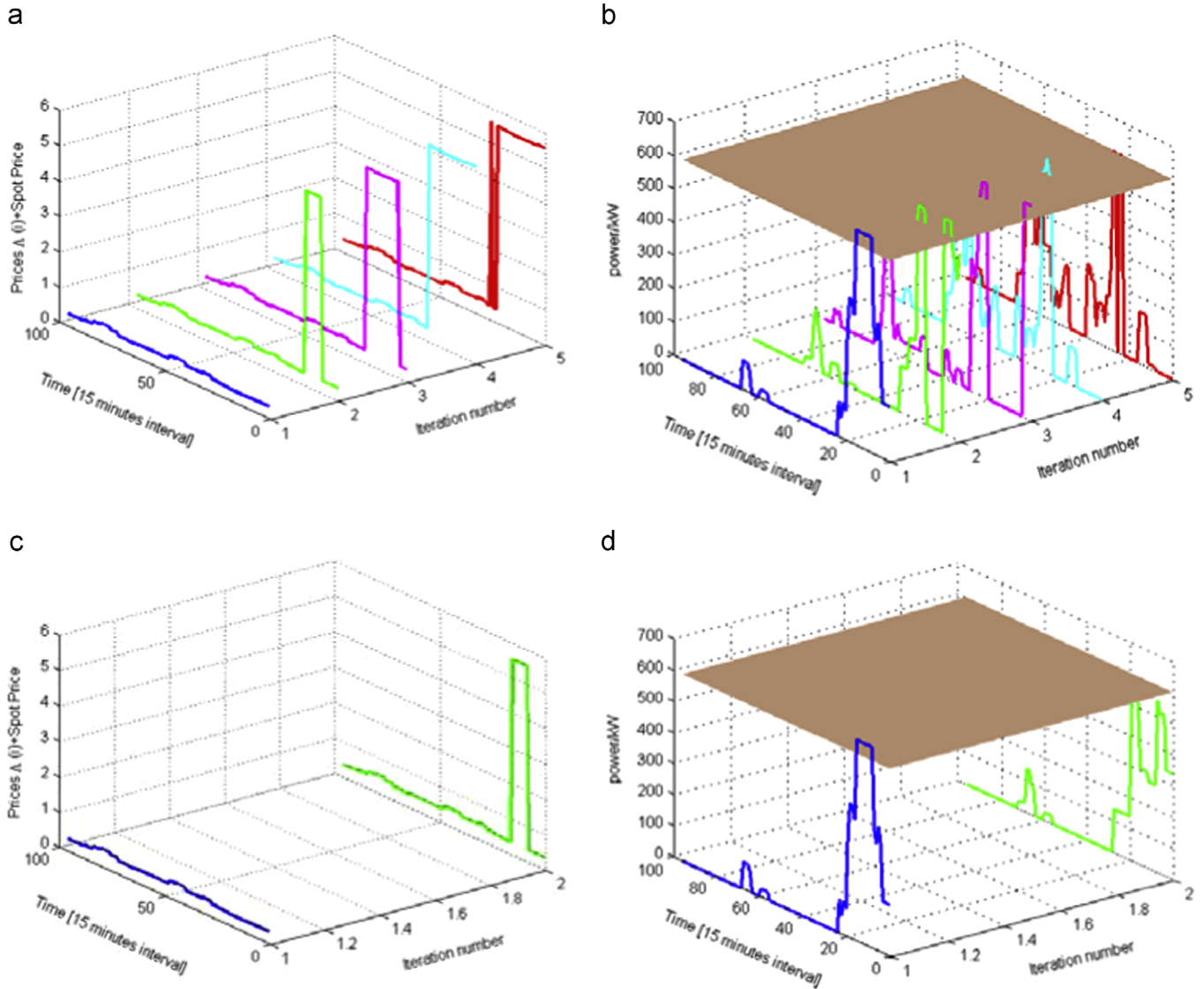
Fig. 9. Case study for centralized control between the FOs and EVs: (a) The sum of the spot price and the shadow price in each iteration step and (b) The comparisons of the FO's power schedule in each step with the power capacity. Case study for decentralized control between FOs and EVs: (c) The sum of the spot price and shadow price in each iteration step and (d) the comparisons of the FO's power schedule in each step with the power capacity.

and trying to avoid charging during the higher price period; as a result, the EVs will be scheduled to charge at a lower price period where congestion can occur as well. In the second case, only some EVs are assumed to respond to the shadow price, which means that only part of the charging plan is rescheduled to the other lower price period, thereby reducing the possibility of causing a new congestion period. Note that in the beginning, the shadow price is zero, so the blue curves in the left part of Fig. 9 represent the spot electricity price. For the remaining price curves, the spikes represent the shadow prices.

5.3. Demonstration result of the MAS

When setting up the demonstration of the multi-agent system, the Simulink part is not included in this case study because the capacity limit is only considered for the transformer. The following two assumptions are used in this case study: (1) there are no power losses in the distribution network, i.e., we do not consider losses, and (2) the overhead lines and underground cables are capable of handling the increasing loads. Based on these assumptions, the power information below the transformer can be simply

obtained by summing up the power schedule of the FOs instead of fetching it from Simulink. For the rest of the system, the process is the same as that presented in Figs. 4–6. In JACK, there are a number of tools available to assist a detailed trace of the system execution, which range from graphical tracing tools to logging tools. In this study, we run the program with the interaction diagram. As we have one DSO agent, one market operator agent, three FO agents, and 14 EV agents, the interaction diagram that shows the communication message among these agents is quite large. It is not wise to show the entire interaction diagram in this paper; instead, we only show part of the interaction diagram where the message sequence occurs between the DSO agent, the market operator agent named CMO, the FO agent FO1, and one EV agent EV1, as shown in Fig. 10. The sequence diagram starts from agent EV1 (which holds for the other 13 EV agents) with a request of schedule calculation. Next, the schedule information is aggregated by the FO agent and is sent to the DSO agent. The rectangular box marked with iteration represents the interactions between the market operator agent and the FO1 agent. This box emulates the negotiation behavior inside a capacity market. When the shadow price is converged, the shadow price is sent to the EV
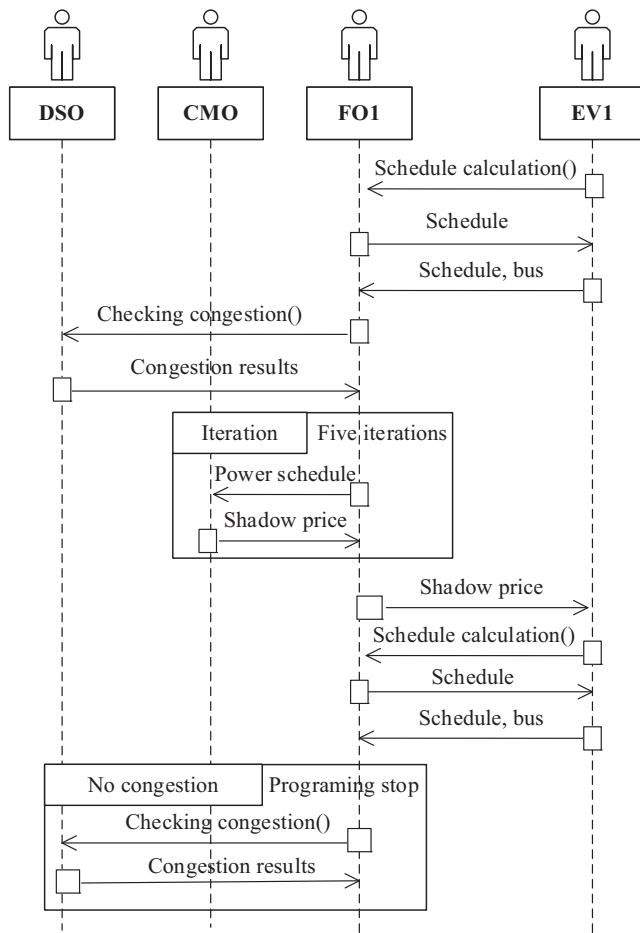
Fig. 10. Sequence diagram between the chosen agents.

agent. With the new schedule, the DSO agent confirms that there will be no congestion for the grid in the planning phase, i.e., the program stops.

6. Discussion and conclusion

A multi-agent system was developed to demonstrate the distributed implementation of the grid congestion management scheme of a distribution network with a large scale deployment of EVs. It is learned from the experience that the distribution grid congestion can be eliminated according to economic principles and that a MAS-based distributed implementation provides significant advantages.

In this study, we develop and utilize an integrated environment consisting of JACK agent software and Matlab to analyze the cyber-physical aspects of the environment; JACK is good for demonstrating the coordination schemes among the actors, and Matlab is good for technical computation of optimization problems. This is a unique contribution of this submission. For a general case, various simulation platforms can be utilized in a distribution grid congestion demonstration. For example, besides JACK, JADE is also widely used for multi-agent simulation. We used JACK because of its capability and support for the explicit modeling of the typical MAS entities, such as agent, plan, event and capabilities. Moreover, in JACK, it is easier to design and analyze interactions and dependencies among such entities. In terms of solving an optimization problem, GAMS also has good performance; however, Matlab is more widely used in the academic field. Finally, the grid modeling tool is also an important part, with the currently existing grid modeling tools including Simulink, MatPower, PowerFactory,

ARISTO, and NEPLAN. Providing these listings is not for a comparison of the various platforms; instead, we want to emphasize that the various tools can be integrated with the MAS settings. There are several highlights in this study compared to the previous studies (Karfopoulos and Hatziargyriou, 2013; Miranda et al., 2011; Greunsven et al., 2012) in term of multi-agent software system development:

1). The developed MAS explicitly presents the relevant agents, the plan, and the event inside a market frame. The modeling approach serves as an example for other similar problems.
2). The developed MAS demonstrates a simulation platform that is based on the integration of JACK, Matlab and Simulink. The platform can integrate the advanced optimization and control and the interactions, which can vary from simple information passing to rich social interactions, such as coordination and negotiation.
3). The developed MAS provides a modeling environment that enables the study of the important characteristics of the proposed distribution grid capacity market, which is not presently available. By implementing and assessing the two level hierarchical control strategy, it is shown that the grid congestion problem can be eliminated in a few steps.

Besides, in this study, market based control method is applied entirely in the hierarchical multi-agents system. The proposed system has the following advantages:

1) The individual EV user's price response behavior is considered which make the study more practical since people's behavior is different.
2) The market based control methods can efficiently allocate the power resources of the transformer and the computational burden is light for the distribution system operator.
3) The simulation result presented in Fig. 9 shows that the proposed method can mitigate the adverse impact of price control where all the EV owners try to charging the EVs in the low price period.

In addition to EVs, some other new loads, such as heat pumps and the increasing electrification of the loads in the home, will also bring challenges to the distribution grid. We believe that this multi-agent framework can be used to address these similar challenges because the use of FOs (You, 2010) (alternative names used for an FO are virtual power plant and aggregator) is also widely proposed for aggregating other distributed energy resources. As expected, the FOs will represent the DERs and interact with the market operator and the DSO similarly to the one in this study.

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