<http://www.diva-portal.org>

Postprint

This is the accepted version of a paper published in *IET Generation, Transmission & Distribution*. This paper has been peer-reviewed but does not include the final publisher proof-corrections or journal pagination.

Citation for the original published paper (version of record):

Hasanpor Divshali, P., Choi, B J., Liang, H. (2017)
Multi-agent transactive energy management system considering high levels of
renewable energy source and electric vehicles
IET Generation, Transmission & Distribution, 11(15): 3713-3721
<https://doi.org/10.1049/iet-gtd.2016.1916>

Access to the published version may require subscription.

N.B. When citing this work, cite the original published paper.

Permanent link to this version:

<http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-219344>

Multi-agent transactive energy management system considering high levels of renewable energy source and electric vehicles

Poria Hasanpor Divshali^{1,2,3}, Bong Jun Choi^{1,2}, Hao Liang⁴

¹Department of Computer Science, The State University of New York Korea, Incheon, Korea

²Department of Computer Science, Stony Brook University, Stony Brook, NY, USA

³Department of Electric Power and Energy Systems, KTH Royal Institute of Technology, Stockholm, Sweden

⁴Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, Canada

E-mail: poriahd@kth.se

Abstract: The future smart grids (SGs) consist of considerable amount of renewable energy sources (RESs), electrical vehicles (EVs), and energy storage systems (ESSs). The uncertainties associated with EVs and uncontrollable nature of RESs have magnified voltage stability challenges and the importance of an effective energy management system (EMS) in SGs as a practical solution. This study presents a multi-agent transactive energy management system (TEMS) to control demand and supply in the presence of high levels of RESs and EVs, and maximises profit of each participant in addition to satisfying voltage regulation constraints. For this purpose, a real-time pricing is considered based on Cournot oligopoly competition model for demand and merit order effect for production to compensate RESs' fluctuations in real time by an indirect control method. Simulations are conducted in the modified IEEE 37-bus test system with 1141 customers, 670 EVs, two solar plants, four wind turbines, and one ESS. The results show that the proposed multi-agent TEMS can indirectly control EVs, elastic loads, and ESSs to balance the RESs oscillation, minimise customers cost, and regulate voltage in a real-time manner. The simulation results also show that the proposed TEMS method can more effectively regulate the voltage than the automatic voltage regulator using a large capacitor bank.

1 Introduction

The traditional transportation system and the conventional power generation system consume a large amount of energy and produce considerable amount of greenhouse gases [1]. Therefore, combination of electrical vehicles (EVs) and renewable energy sources (RESs) has a high potential to reduce energy cost and greenhouse gases. Although these benefits have been increasing the level of RESs in the power systems, the technical issues such as the voltage violation of distribution grid beyond the boundaries set by standards (e.g. EN 50160 [2]), limit RESs penetration. Various approaches, such as installing capacitor bank and on-line tap changer for LV transformers, are proposed in literature to mitigate this problem. However, since EVs and elastic loads can be controlled in the smart grid (SG) to balance the RESs output power, the voltage profile can be regulated by implementing an appropriate energy management system.

In the SG, the energy management system (EMS), which can jointly control the loads, energy sources, and energy storage systems (ESSs), plays a critical role. However, some literature in this area only investigates supply side management (SSM) programme and does not pay attention to the potential of elastic loads to improve the RESs conditions. Macedo *et al.* [3] present a mixed-integer non-linear programming model to solve the optimal operation of a radial distribution networks including RESs and ESSs. A stochastic unit commitment for SGs in the presence of RESs is proposed in [4, 5] based on Markovian transition probability matrix.

On the other hand, some other literature controls sources and loads all together. A hierarchical optimisation method is used to minimise the cost of a grid considering the demand response (DR) with a centrally shared wind turbine and an ESS in [6]. Yang *et al.* [7] model various devices in microgrids, e.g. elastic appliances, batteries, and wind turbines, and develop a large-scale mixed-integer programming optimisation problem to minimise the total economic cost of the grid. However, this method does not allow customers to make local decisions and neglects the power system

constraints. A multi-agent-based SSM for conventional power sources in the power system having ESSs and incentive-based DR programme is developed in [8] to reduce the system peak and cost. However, incentive-based DR is not appropriate for the residential sector [9] due to the difficulty of calculating the exact values of each load. Also, an SSM programme considering EVs and RESs is formulated in [10] to minimise the expected operational cost of the SG over the next 24 h, while other elastic loads are not considered in the programme.

Generally, implementing DR in EMS, especially due to a large number of consumers, makes the management problem much more complicated. Most of the research in this area has common major drawbacks. Firstly, some critical technical issues are neglected to simplify mathematical calculations. However, high-penetration levels of RESs and EVs have significant influences on the power system and should be accounted in the mathematical formulation [11]. Secondly, many EMSs use the direct control method where retailers control the elastic loads of their region directly from a central entity. However, the direct methods take away the decision authority from customers and can adversely affect the popularity and security of the management system [12]. As a result, the indirect charging methods are more likely to be accepted by customers than the direct methods [13]. Thirdly, most EMSs select the welfare of the whole network as their objective and do not allow participants to autonomously minimise its own cost. This may discourage customers to participate in the EMS. A review on the contemporary research in EMS of SGs including the future research directions is presented in [14]. As a result, an indirect real-time pricing (RTP)-based technique using two-way communications, called the transactive control [15], is suggested to be the best approach to manage demand, supply, and ESSs in SGs. The gridwise architecture council defines the transactive energy framework for the SG in [16].

Implementing the transactive EMS (TEMS) is highly complex. In indirect methods, all customers try to optimise their own cost. Therefore, they may make similar decisions and collectively produce a significant impact on the system, called avalanche effect

[13] or rebound peak [17]. As a result, considering the effects of all customers' decision is significantly important when implementing indirect control methods. Under these circumstances, the TEMS has to use imperfect competition, or oligopoly market model, which considers the effect of each participant on the electricity market. The implementation of an oligopoly model is much more complicated than a perfect one. The Cournot competition model is one of the popular oligopoly models on the production side used to describe a market in which companies compete independently to maximise their own profit [18]. However, using this model on the customer side, having many participants, is a complicated process. The authors of [19] proposed a Cournot competition to model a dynamic price for an intelligent building with RESs, ESSs, and loads. However, they did not consider EVs, and made some simplifying assumptions to solve the problem, which limits the practical implementation of their technique.

Therefore, this paper formulates the TEMS based on oligopoly model for the demand side and the merit order effect for the supply side. In particular, this paper proposes a new heuristic multi-agent technique to find the optimum power of customers, generation units, and ESSs in a decentralised real-time manner such that the customers' cost is minimised and the voltage profile of the power system is well regulated. The main contributions of this paper are summarised as follows:

- Propose TEMS to control elastic appliances, EVs, productions, and ESSs, simultaneously.
- Consider the effect of customers' decision in the market using Cournot imperfect competition model.
- Model effects of a high-penetration level of RESs using the merit order effect.
- Give the decision authority to all customers by using an indirect method.
- Minimise the cost of each participant, individually, instead of the total network cost.
- Consider the non-linear power technical constraints and prevent rebound peaks.
- Propose a heuristic iterative multi-agent method to quickly obtain RTP.

This paper is organised as follows: The TEMS formulation is presented in Section 2. A proposed heuristic method to solve the optimisation problem of TEMS is presented in Section 3. The simulation network and the performance evaluation results are detailed in Section 4. Finally, the conclusions are made in Section 5.

2 Oligopoly TEMS model

In the proposed TEMS, all energy producers participate in a real-time market by submitting bids to supply some amount of energy at some price for the duration of period under consideration. On the other hand, customers schedule their appliances to minimise their individual cost by considering the influence of other consumptions based on Cournot oligopoly model. Moreover, the TEMS employs an RTP and indirectly controls elastic loads, EVs, and ESSs to match their consumption with RESs' fluctuations while satisfying the power system constraints. This section describes the mathematical formulation of different participants in the SG to obtain the equilibrium.

2.1 Household demand model

Each customer has two different types of loads: inelastic where its operation schedule cannot be shifted in time (e.g. lighting) and elastic where its operation schedule can be shifted during some defined periods (e.g. dishwasher). Customers try to minimise their own cost by shifting the operation schedule of elastic appliances to the periods with lower prices while taking the effect of other consumptions into account. Many appliances have a continuous working period, meaning that once an appliance starts its operation, it continues until its given task is complete. As a result, each customer (i th customer) should determine the optimum starting

time of one of its elastic loads (k th appliance) to minimise the cost. As the task on the load should be completed before its desired finishing time ($t_{\text{end},ik}$), the starting time ($t_{0,ik}$) should be selected as

$$t \leq t_{0,ik} < t_{\text{end},ik} - t_{d,ik} \quad \forall k, \quad (1)$$

where t is the current time and $t_{d,ik}$ is the time duration that the k th appliance of i th customer needs to complete its task. In addition, customers also have a specific maximum allowable apparent power ($S_{\text{max},i}$), which should be satisfied. The scheduling of appliances is described in more detail in [20].

2.2 ESS and EV model

The formulation of battery ESSs and plug-in EVs is similar. The input power of the i th ESS/EV system should stay between the maximum charging and discharging capacity ($p_{\text{max},ch,i}$ and $p_{\text{max},dch,i}$) as

$$p_{\text{max},dch,i} \leq p_{\text{ESS},i}(\tau) \leq p_{\text{max},ch,i} \quad \forall \tau \quad (2)$$

where $p_{\text{ESS},i}$ is the output power of ESS/EV. The battery's state of charge (SOC), which can be modelled as below, should stay between its minimum and the maximum values ($\text{SOC}_{\text{min},i}$ and $\text{SOC}_{\text{max},i}$) and should reach a desired value ($\text{SOC}_{d,i}$) before a certain time ($t_{d,i}$) (e.g. EV's departure time)

$$\text{SOC}_i(\tau + 1) = \text{SOC}_i(\tau) + \left(S_{\text{ch}}\eta_{\text{ch}} + \frac{(1 - S_{\text{ch}})}{\eta_{\text{dch}}} \right) P_{\text{EV},i} \quad \forall \tau \quad (3)$$

$$\text{SOC}_{\text{min},i} \leq \text{SOC}_i(\tau) \leq \text{SOC}_{\text{max},i} \quad (4)$$

$$\text{SOC}(t_{d,i}) \geq \text{SOC}_{d,i} \quad (5)$$

where η_{ch} and η_{dch} are the efficiency of the charger in a charging mode (G2V) and a discharging mode (V2G), respectively, and S_{ch} is an indicator binary state variable that equals to 1 when charging and 0 otherwise. In addition, the lifetime of a battery degrades with charging and discharging operations [21]. Therefore, the battery degradation cost ($C_{d,i}$) calculated as below is later added to the cost function

$$C_{d,i}(t) = r_b \cdot P_{\text{ESS},i}(t) \cdot \eta_{\text{dch}}, \quad (6)$$

where r_b is the degradation coefficient based on \$/kW. Since in G2V mode, the battery charging and discharging is a requirement for working of EVs, the degradation cost is only added in V2G modes. Finally, the charging and discharging powers should satisfy the constraint on the maximum allowable apparent power ($S_{\text{max},i}$) as

$$\left(p_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(\tau) + p_{\text{ESS},i}(\tau) \right)^2 + \left(Q_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} Q_{e,ik}(\tau) + Q_{\text{ESS},i}(\tau) \right)^2 \leq S_{\text{max},i}^2 \quad \forall \tau, \quad (7)$$

where $P_{ie,i}$, $Q_{ie,i}$, $P_{e,ik}$, $Q_{e,ik}$, $P_{\text{ESS},i}$ and $Q_{\text{ESS},i}$ are the active and reactive powers of inelastic loads, k th elastic appliance, and ESS/EV of i th customer, respectively, and $n_{e,i}$ is the number of elastic loads of i th customer.

2.3 SSM model

An interconnected SG has various sources to provide the power required for demands: (i) power purchased from the electrical market or other grids, (ii) local generators, (iii) local RESs, and (iv) power stored in ESSs/EVs. Scheduling these sources in such a way that minimises the cost and satisfies all grid constraints is called

Fig. 1 Merit order effect caused by the participation of RESs

SSM. Generally, controllable generators participating in a local real-time market try to maximise their profit by submitting bids to supply with a certain amount of electrical energy at their marginal cost (MC). Then, the SG operator ranks bids in the order of increasing price. From this ranking, a curve showing the bid price as a function of the cumulative bid quantity, called the supply curve of the controllable generator, can be constructed [18]. In this method, the power purchased from other grids can be considered as power from a local controllable generator in the common coupling bus.

The output power of renewable energy, such as wind turbines or solar systems, cannot be controlled and it is fluctuated depending on the climate. However, since the RESs have negligible production cost, they can participate in the local market with zero MC. Then, RESs can help to lower the energy cost by shifting the supply curve towards the right on the horizontal axis. This effect, called RESs' merit order effect [22], is illustrated in Fig. 1.

Consequently, the RTP ($\pi(t)$) can be calculated from the given supply curve (S) as

$$\pi(t) = S \left(\sum_{i=1}^n \left(P_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t) + P_{ESS,i}(t) \right) - \sum_{i=1}^{n_{R,i}} P_{RES,i}(t) + P_{loss}(t) \right) \quad (8)$$

where n is the number of customers, $P_{RES,i}$ is the active power output of i th RES, n_R is the number of RESs, and P_{loss} is the total power loss of the electrical grid.

2.4 power system network model

The proposed TEMS computes the power loss and the power system constraints using a backward/forward sweep method [23], which is one of the most popular methods used for radial distribution networks. The power loss of the network is calculated as

$$P_{loss} = \sum_{i=1}^m \sum_{k=1}^m |V_i| |V_k| |Y_{ik}| \cos(\delta_i - \delta_k - \theta_{ik}), \quad (9)$$

where $|V|$ and δ are the magnitude and phase of the bus voltage, respectively; m is the number of network buses, and $|Y|$ and θ are the magnitude and phase of the grid admittance matrix, respectively. In addition, the current and voltage regulation constraints on branches are, respectively, as follows:

$$|I_k(\tau)| < I_{k,max} \quad \forall \tau, \quad (10)$$

$$V_{min} < |V_j(\tau)| < V_{max} \quad \forall \tau, \quad (11)$$

where $|I_k|$ is the magnitude of k th branch current, $I_{k,max}$ is the k th branch capacity, V_{min} and V_{max} are the minimum and maximum levels of the network voltage, respectively.

2.5 TEMS model

Finally, by combining the models of SG components presented in previous subsections, the mathematical model of the TEMS using the Cournot oligopoly competition model for each demand and the merit order effect for energy supply units is formulated as follows: (see (12)) where $\pi^p(\tau)$ is the predicted energy price for future times. The equilibrium point or RTP ($\pi(t)$) of the SG can be calculated from solving the optimising problem (12) simultaneously for all participants. This is a non-linear non-convex optimisation problem with many variables for each participant, e.g. each customer. The RTP is obtained by solving the corresponding optimisation problem for all participants in a same time, in other words, a multi-objective non-linear non-convex optimisation problem. This multi-objective optimisation problem cannot be solved in this form.

3 Proposed heuristic iterative multi-agent method

This section presents a proposed heuristic iterative multi-agent method that quickly solves the TEMS (the optimising problem (12) for all participants) in real-time applications. First, each demand agent (energy consumer) solves a modified optimisation problem, which neglects the network constraints and the dependency of the price to other participants. Then, the grid agent gathers the results from all demand and supply agents, and updates RTP. Using the results of all demand and supply agents, the grid agent compensates the modifications, which are previously made by each consumer, in an iterative manner. Fig. 2 illustrates the overall mechanism of the proposed heuristic iterative multi-agent method.

3.1 Demand agent operation

In the demand side, participants try to minimise their cost based on the local constraints and the given price. In this case, the optimisation problem of (12) converts to (13) as follows: (see (13)) where $\pi_d(\tau)$ is a given market price that is updated by the grid agent by considering the dependency with other participants and network constraints for time interval t . A heuristic method to quickly find the solution of (13), such that it can be implemented in simple computing devices like smart meters, is detailed as follows.

3.1.1 Algorithm 1, elastic appliances scheduling: Since elastic appliances have continuous operation periods, their optimal starting times have to be scheduled. For this purpose, the proposed method gives a higher priority to those appliances that need to finish their tasks earlier than that of others. In other words, the earliest deadline first method, which is one of the traditional real-time scheduling method in the field of computing systems [24], is used to minimise the cost of elastic loads while satisfying the local constraints defined in (7) regardless of ESSs or EVs. More details about this method can be found in [20]. The elastic appliance scheduling carried out by demand agents is shown in Algorithm 1.

Algorithm 1: Demand agent operation – Part 1, elastic appliances scheduling

1: Arrange the appliances in order of increasing $(t_{end,ik} - t_{d,ik})$

Fig. 2 Overall mechanism of the proposed iterative multi-agent method to solve TEMS

$$\begin{aligned}
 \text{Min}_{t_{0,ik}, P_{ESS,i}(t)} \text{Obj} = & \left(P_{ESS,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t) \right) \cdot \pi(t) + \sum_{k=1}^{n_{e,i}} \sum_{\tau=t}^{t+t_{d,ik}} P_{e,ik}(\tau) \cdot \pi^P(\tau) + C_{d,i} \\
 \text{s.t.} \quad & \pi(t) = S \left(\sum_{i=1}^n \left(P_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t) + P_{ESS,i}(t) \right) - \sum_{i=1}^{n_{R,i}} P_{RER,i}(t) + P_{loss}(t) \right), \\
 & P_{loss} = \sum_{i=1}^m \sum_{k=1}^m |V_i| |V_k| |Y_{ik}| \cos(\delta_i - \delta_k - \theta_{ik}), \\
 & |I_k(\tau)| < I_{k,max} \quad \forall \tau, \\
 & V_{min} < |V_j(\tau)| < V_{max} \quad \forall \tau, \\
 & \left(p_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(\tau) + P_{ESS,i}(\tau) \right)^2 + \left(q_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} q_{e,ik}(\tau) + Q_{ESS,i}(\tau) \right)^2 \leq S_{max,i}^2 \quad \forall k, \forall \tau, \\
 & P_{max,dch,i} \leq P_{ESS,i}(\tau) \leq P_{max,ch,i}, \\
 & SOC_i(\tau+1) = SOC_i(\tau) + (S_{ch}\eta_{ch} + (1 - S_{ch})/\eta_{dch})P_{EV,i}, \\
 & SOC_{min,i} \leq SOC_i(\tau) \leq SOC_{max,i}, \\
 & SOC(t_{d,i}) \geq SOC_{d,i}, \\
 & t \leq t_{0,ik} < t_{end,ik} - t_{d,ik}, \quad \forall k.
 \end{aligned} \tag{12}$$

$$\begin{aligned}
 \min_{t_{0,ik}, P_{ESS,i}(t)} \text{Obj} = & \left(P_{ESS,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t) \right) \cdot \pi_d(t) + \sum_{k=1}^{n_{e,i}} \sum_{\tau=t}^{t+t_{d,ik}} P_{e,ik}(\tau) \cdot \pi^P(\tau) + C_{d,i} \\
 \text{s.t.} \quad & \left(p_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(\tau) + P_{ESS,i}(\tau) \right)^2 + \left(q_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} q_{e,ik}(\tau) + Q_{ESS,i}(\tau) \right)^2 \leq S_{max,i}^2 \quad \forall k, \forall \tau, \\
 & P_{max,dch,i} \leq P_{ESS,i}(\tau) \leq P_{max,ch,i}, \\
 & SOC_i(\tau+1) = SOC_i(\tau) + (S_{G2V}\eta_{ch} + (1 - S_{G2V})/\eta_{dch})P_{EV,i}, \\
 & SOC_{min,i} \leq SOC_i(\tau) \leq SOC_{max,i}, \\
 & SOC(t_{d,i}) \geq SOC_{d,i}, \\
 & t \leq t_{0,ik} < t_{end,ik} - t_{d,ik}, \quad \forall k.
 \end{aligned} \tag{13}$$

2: **For** $k = 1$ to $n_{e,i}$ **do**

3: Calculate $\sum_{\tau=t_{0,ik}}^{t_{0,ik}+t_{d,ik}} P_{e,ik}(\tau) \cdot \pi(\tau)$ for

$t_{0,ik} \in (t, t_{\text{end},ik} - t_{d,ik})$.

4: Check the constraint (7) for all $\tau \in (t_{0,ik}, t_{0,ik} + t_{d,ik})$.

5: Select the cheapest costs that satisfies (7).

3.1.2 Algorithm 2, ESSs and EVs scheduling: Determining the amount of charging and discharging of batteries is done in two steps. The step one makes sure that the battery is charged up to the desired value before its deadline (t_d), while the step two calculates the amount of discharging and the equivalent amount of charging to maintain the same charging level at the end of the desired time. The desired energy at the end of each day is assumed equal to the initial energy, and thus the first step is initially done. However, the net energy that should be charged in i th EV battery ($E_{t,i}$) calculated as

$$E_{t,i} = \text{SOC}_{d,i} - \text{SOC}_{0,i} \quad (14)$$

should be scheduled to the most appropriate time. Since batteries should be charged in periods with the lowest price as much as possible to minimise the energy cost, the algorithm assigns $E_{t,i}$ to the time periods with the lowest price first. In each time period, the output energy of battery ($P_{\text{ESS},i}(t)$) is calculated to satisfy all local constraints as follows: (see (15)) After assigning some power to the time interval τ , $E_{t,i}$ and $P_{\text{max},ch,i}(\tau)$ are updated as

$$E_{t,i}^{\text{new}} = E_{t,i} - \min(E_{t,i}, P_{\text{EV},i}(\tau)), \quad (16)$$

$$P_{\text{max},ch,i}^{\text{new}}(\tau) = P_{\text{max},ch,i}(\tau) - \min(E_{t,i}, P_{\text{EV},i}(\tau)). \quad (17)$$

Here, if $E_{t,i}^{\text{new}}$ is greater than zero, the period with the next cheapest price is used and this procedure continues until $E_{t,i}^{\text{new}}$ becomes zero. At the end of step one, the battery's SOC is calculated from (3).

To balance the power market, ESSs/EVs sell the energy in periods with high prices and replace it from periods with low prices. This task would be reasonable when the difference of these prices could compensate the loss of charging and discharging processes including the cost of degradation. The net profit from selling some energy in time t_h and buying the equivalent amount of energy in time t_l can be calculated as

$$\text{Profit}_{V2G,i}^{\text{hl}} = P_{\text{sell},i}^{\text{hl}} \cdot (\pi(t_h) - r_b/\eta_{\text{dch}} - \pi(t_l)/\eta_{\text{ch}} \cdot \eta_{\text{dch}}), \quad (18)$$

where $P_{\text{sell}}^{\text{hl}}$ is the amount of energy that i th ESS/EV sells in period t_h according to all local constraints and it is obtained as (see (19)) The step two orders all possible combination of (t_h, t_l) so that the pair with the biggest $(t_h - t_l)$ is listed first. Sequentially from the list, until $\text{Profit}_{V2G,i}^{\text{hl}} > 0$, the algorithm updates $P_{\text{EV},i}$, $P_{\text{max},dch,i}(t_h)$, and $P_{\text{max},ch,i}(t_l)$, from (20)–(23) and SOC of battery from (4). Algorithm 2 outlines how the demand agents optimise the ESSs/EVs power. More details of this algorithm is described in [25]

$$P_{\text{EV},i}(t_h) = P_{\text{EV},i}(t_l) + P_{\text{sell}}^{\text{hl}}, \quad (20)$$

$$P_{\text{EV},i}(t_l) = P_{\text{EV},i}(t_l) + \frac{P_{\text{sell}}^{\text{hl}}}{(\eta_{\text{ch}} \cdot \eta_{\text{dch}})}, \quad (21)$$

$$P_{\text{max},dch,i}^{\text{new}}(t_h) = P_{\text{max},dch,i}(t_h) - P_{\text{sell}}^{\text{hl}}, \quad (22)$$

$$P_{\text{max},ch,i}^{\text{new}}(t_l) = P_{\text{max},ch,i}(t_l) - \frac{P_{\text{sell}}^{\text{hl}}}{(\eta_{\text{ch}} \cdot \eta_{\text{dch}})}. \quad (23)$$

Algorithm 2: Demand agent operation – Part 2, ESSs and EVs scheduling

- 1: Calculate $E_{t,i}$ from (14).
- 2: Arrange the time periods in order of increasing price.
- 3: **While** $E_{t,i} > 0$ **do** (sequentially from the arranged list)
- 4: Calculate $P_{\text{EV},i}(t)$ from (15).
- 5: Update $E_{t,i}$ and $P_{\text{max},ch,i}(t)$ from (16) and (17).
- 6: Calculate the SOC for all periods from (3).
- 7: Arrange all possible combinations in order of decreasing (t_h, t_l)
- 8: **While** $\text{Profit}_{V2G,i}^{\text{hl}} > 0$ **do** (sequentially from the arranged list)
- 9: Calculate $\text{Profit}_{V2G,i}^{\text{hl}}$ from (18) and (19).
- 10: Update $P_{\text{EV},i}$, $P_{\text{max},dch,i}(t_d)$, and $P_{\text{max},ch,i}(t_l)$ from (20) to (23).

3.2 Supply agent operation

In each time interval, controllable generators should participate in the local market by submitting bids to supply a certain amount of electrical energy at their MC. RESs or uncontrollable generators participate in the market by submitting the short-term prediction of energy production with zero MC. Since the EMS runs on each short-time interval, the short-term prediction has almost no error.

The supply agent, based on the merit order effect, lists bids of controllable production units including the power purchased from other grids in the order of increasing price. Then, it selects the price of the market from the total amount of demand, power loss, and the predictions of RESs energy production. Algorithm 3 details the supply agent operation.

Algorithm 3: Supply agent operation

- 1: Gather bids of controllable production units.
- 2: Arrange bids in order of increasing price.
- 3: Collecting the short-term prediction of RESs' output power.
- 3: Calculate the grid price from (8)

3.3 Grid agent operation

The grid agent compensates the modifications were done in demand agents. As discussed in subsection 3.1, demand agents solve the problem locally; therefore, it is necessary to compensate these modifications and to implement the effect of grid constraints and other customers' decisions in TEMS. These effects are considered in the grid agent by updating RTP to converge to the equilibrium point where the supply and the demand match. For this purpose, the agent calculates the total power using a power flow method, and receives the supply price (π_s) from the supply agent. If

$$P_{\text{ESS},i}(t) = \min(E_{t,i}/\eta_{\text{ch}}, P_{\text{max},ch,i}, P_{\text{max},i}(\tau)),$$

$$P_{\text{max},i}(\tau) = \sqrt{S_{\text{max},i}^2 - \left(Q_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} Q_{e,ik}(\tau)\right)^2} - \left(P_{ie,i}(\tau) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(\tau)\right). \quad (15)$$

$$P_{\text{sell},i}^{\text{hl}} = \begin{cases} \min(\min(\text{SOC}_i(t_h; t_{d,i}) - \text{SOC}_{\min,i}) \cdot \eta_{\text{dch},i} \cdot P_{\text{max},dch,i}(t_h), P_{\text{max},ch,i}(t_l) \cdot \eta_{\text{ch},i} \cdot \eta_{\text{dch},i} \cdot P_{\text{max},i}^{\text{new}}(\tau) - P_{\text{EV},i}(\tau)) & t_h > t_l \\ \min(\min(\text{SOC}_{\max,i} - \text{SOC}_i(t_l; t_{d,i}))/\eta_{\text{ch},i} \cdot P_{\text{max},dch,i}(t_h), P_{\text{max},ch,i}(t_l) \cdot \eta_{\text{ch},i} \cdot \eta_{\text{dch},i} \cdot P_{\text{max},i}^{\text{new}}(\tau) - P_{\text{EV},i}(\tau)) & t_h < t_l \end{cases} \quad (19)$$

Fig. 3 Demand and supply curve in a rational power market
(a) A general form, (b) When customers make similar decisions

Fig. 4 Modified IEEE-37 bus test system

Fig. 5 Profiles of RESs and elastic appliances in the test system

(a) Production by wind turbines, (b) Production by solar panels, (c) Average consumption by elastic appliances

π_s is equal to π_d , the equilibrium point is found. Otherwise, the algorithm updates the price for the next iteration to approach the equilibrium point.

The equilibrium point (π^*) is the intersection of the supply curve, which is a non-decreasing function, and the demand curve, which is a non-increasing function, as shown in Fig. 3a. The equilibrium can be found by bisecting the difference between these two prices ($\pi_s - \pi_d$) as proved in the Appendix. Algorithm 4 details the process of updating the price (π^{new}) to converge to the equilibrium via an iterative process, where, π_{min} and π_{max} are the upper and lower limit of the equilibrium price, respectively. In addition, in order to control power system constraints, as shown in [26], the price of some loads (nodes) can be changed. Therefore, a controlling price can be added to RTP in this part of the algorithm to satisfy the network constraints.

Algorithm 4: Grid agent - Part 1, π^{new} , π_{min} , π_{max} calculation

- 1: **For** $i = 1$ to k (k = the iteration count) **do**
- 2: **If** $\pi^i < \pi^{i+1}$ **then** $\pi_{min} = \min(\pi_{min}, \pi^i)$
- 3: **If** $\pi^i > \pi^{i+1}$ **then** $\pi_{max} = \max(\pi_{max}, \pi^i)$
- 4: $\pi^{new} = (\pi_{min} + \pi_{max}) / 2$

Algorithm 4 always converges to the equilibrium price. However, when the customers make similar decisions, there are

sudden changes in the demand curve as shown in Fig. 3b, and the consumption power corresponding to π_{min} and π_{max} consequently is not similar. Algorithm 5 tackles this problem by considering π_{max} (or π_{min}) as the equilibrium price and calculating the equilibrium power (P^*) from the inverse supply curve. Then, the difference between P^* and $P(\pi_{max})$ (or $P(\pi_{min})$), defined as residual power, is allocated to some random customers by changing the price of some customers from π_{max} to π_{min} . This little change has no effect on the market price but changes the power consumption of the grid.

Algorithm 5: Grid agent – Part 2, residual power allocation

- 1: Select π_{max} as π^* .
- 2: Calculate $P(\pi_{max})$ from demand agent.
- 3: Calculate P^* from supply agent.
- 4: $P_{res} = P^* - P(\pi_{max})$
- 3: **While** $P_{res} > 0$ **do**
- 4: Select an participant randomly, change its price to π_{min} , and calculate $P_i(\pi_{max})$.

$$5: \quad P_{res} = P_{res} - (P_i(\pi_{min}) - P_i(\pi_{max}))$$

The grid agent needs to provide market price prediction for all demand agents. The discussion about market price prediction algorithms are out of scopes of this paper. Here, it is suggested to use the results of demand agents (Algorithms 1 and 2) for whole time period instead of only the current interval. By this method, the network agent can access a future consumption and improve the price forecasting.

4 Performance evaluation

4.1 Simulation setup

The simulation is conducted under a modified IEEE-37 bus test system, as shown in Fig. 4, using MATLAB on a workstation with an 8-core 2.3 GHz CPU and 8 GB RAM. On the bus test system, four wind turbines, two solar panels, and one 100 kW central ESS are added. The profiles of RESs are taken from Australian energy market operator [27] and are shown in Fig. 5. Inelastic load profiles are generated based on the household model presented in [28, 29], such that the maximum power of each bus is equal to the nominal power of the test system. This procedure results in 1141 customers consuming about 11.2 MWh a day.

Elastic loads dishwashers (wet1) and clothes washers/dryers (wet2) are modelled using the average consumption profile as shown in Fig. 5c. We assume that 23% of customers use the wet1

Fig. 6 The simulation results of the proposed TEMS in comparison to the FP

(a) Active power of the grid, (b) MC of the grid, (c) Active power of wet appliances and EVs, (d) Number of iteration and calculation time for each time interval in the proposed TEMS

between 6 and 8 p.m. and the dishes need to be cleaned before the next day between 6 and 9 a.m. with a uniform distribution. The wet2 appliances are plugged in between 8 and 10 a.m. with the probability of 28% and their tasks should be done before 2 and 5 p.m. with a uniform distribution. Under these assumptions, all wet appliances consume about 2 MWh a day.

For EVs, we assume that 50% of customers have EVs (670 EVs). The departure and arrival times of EVs are set to a value generated using a normal distribution with a standard deviation of 1 h and a mean of 7 a.m. and 7 p.m., respectively. The SOC_d is selected between 60 and 100% with a uniform distribution and SOC_0 is set to a value generated using a normal distribution with a mean of 10 kWh and the standard deviation of 2 kWh less than SOC_d . A typical EV with the energy consumption rate of 0.36 kW/mile [30] having 10 kWh of energy can travel 28 miles, which is the average commuting distance. The maximum of charging power, house demand, and battery size is selected randomly among ($p_{max} = 2$ kW, $S_{max} = 5$ kVA, $SOC_{max} = 10$ kWh), ($p_{max} = 9$ kW, $S_{max} = 10$ kVA, $SOC_{max} = 20$ kWh), and ($p_{max} = 9$ kW, $S_{max} = 10$ kVA, $SOC_{max} = 30$ kWh). The charging and discharging efficiency is selected to be 95% and the degradation coefficient is set to 0.05 \$/kW (the minimum amount) [21]. The supply curve is calculated so that the average energy price bought from the upper network in the base situation (without RESs and EVs) for off-peak and peak time equal to 4 and 17 ¢/kW according to [31]. Under this consumption, the merit order effect are modelled as

$$S(P_{total}) = 1.88E - 7(P_L - P_{RESs} - P_{ESSs} + P_{loss})^2 + 3.67E - 5(P_L - P_{RESs} - P_{ESSs} + P_{loss}) + 4.12E - 2, \quad (24)$$

where P_L , P_{RESs} , and P_{ESSs} are the total consumption, generation of RESs, and ESSs output power, respectively. Since the prediction of inelastic load consumptions and RESs production are used in the price forecasting, the price forecast in the simulation is modelled using 3% error. Note that here the price forecast is calculated by repeating the whole TEMS method several times, starting with an initial price guess and repeatedly updating the price forecast.

4.2 Simulation results

The performance of the proposed TEMS is compared with the system without EMS (flat pricing (FP) method) where there is no incentive for customers to adjust their consumption with RESs'

fluctuations. Consequently, as shown in Fig. 6, elastic appliances consume energy as soon as they connect to the grid and create a peak (856 kW) in early mornings. However, at noon, because of the high production by solar panels, the amount of production exceeds the consumption and the grid injects power (71 kW) to the upper network. However, injecting power to the upper network, in addition to decreasing the profit of generation due to low RTP of the market, creates some technical problems, such as voltage increase [32] and the protection malfunction. A same trend with a higher peak (2490 kW) can be observed in evenings because of EVs' load and a high-power injection (273 kW) to the upper network due to low-energy consumption. However, the proposed TEMS, as shown in Fig. 6a, balances the production and consumption by yielding a nearly flat profile with 612 kW peak. The MC of the TEMS shown in Fig. 6b and the original and shifted profile of elastic loads and EVs are shown in Fig. 6c. These figures show how the grid agent can indirectly controls demand agents to match their consumptions with RESs and other productions by adequately changing the RTP (MC). Note that this simulation did not implement any additional controlling price proposed in [26], to improve network constraints since the method improves naturally the constraints by matching the consumptions with production profiles. However, there is further possibility in this method by changing the price of different nodes to control their consumptions and to prevent constraints in the grid.

Moreover, the calculation time is an important factor for the TEMS using RTP method. As shown in Fig. 6d, the proposed method runs in the order of seconds and is quick enough for real-time usage. It is worth mentioning that the calculation of demand agents (Algorithms 1 and 2), which may run on smart meters, is very simple and each run takes <0.01 s on average.

Table 1 is a summary of performance calculation showing that the proposed TEMS can smooth the MC and the consumption profile of the grid and decrease the energy cost and loss. Since the difference between the maximum and minimum RTP is only \$0.044, the operation of ESS would not be profitable due to the degradation cost and the efficiency of charging and discharging processes, even with errorless price forecasting. This is why the output power of ESS as shown in Fig. 6c is always zero and the EVs do not operate in V2G mode.

Distribution grids face overconsumption or overproduction problem, which causes voltage violation without TEMS. This voltage violation could be so severe that even other methods, such as installing a large capacitor bank using automatic voltage regulator, may not be able to solve the problem. Fig. 7a compares the worst bus voltage profile, which is the bus with the largest

Table 1 Performance comparison of the proposed TEMS with FP

Cases	P, kW		Q, kVAR		MC _{max} , \$/kW	Loss, kWh	V, %		Cost, \$		Non-RESS	
	min	max	min	max			min	max	Inelastic	Wet 1	Wet 2	EVs
FP	-273	2490	45	590	1.117	493	89.0	101.2	2043	512	94	3418
TEMS	78	583	89	490	0.084	171	96.7	99.7	592	73	54	437

Fig. 7 The simulation results of the proposed TEMS in comparison to FP
(a) The worst bus voltage profile, (b) The total reactive power consumption

voltage difference during the time in the FP, transactive method, and installing an extra-large capacitor bank (400 kVAR) in the critical bus. In FP method, the voltage fluctuates between 0.89 and 1.01 p.u. and the capacitor bank using automatic voltage regulator injects up to 400 kVAR reactive power and voltage is kept between 0.91 and 0.996, while the transactive method contains this variation between 0.957 and 1.004 p.u. Moreover, the proposed TEMS shifts the demand to match the production profile and, by solving the overconsumption or overproduction problem, removes the source of voltage violation. The total reactive power consumption of the grid considering that RESs do not produce reactive power and EVs can charge their battery at unit power factor as shown in Fig. 7b.

5 Conclusion

The increasing number of RESs and electrical demands like EVs makes the EMS more imperative in the future SGs. This paper proposes a TEMS using an oligopoly competition market in demand side and a merit order effect in supply side of an SG having a high-penetration level of RESs and EVs. The indirect control method gives the decision authority to customers to attract more participants while the oligopoly competition model considers the effect of all participants' decision to prevent rebound peak and satisfy the power system constraints. Since the TEMS formulation leads to a complicated non-linear non-convex multi-objective optimisation problem, a heuristic iterative multi-agent method is proposed to solve the problem quickly. The method is implemented in MATLAB on the modified IEEE 37-bus test system including 1141 customers with different appliances, 670 EVs, two solar panels, four wind turbines, and one ESS. The simulation results show that the proposed method indirectly enables demand to effectively trail the RESs' fluctuations and decreases the power loss and energy cost while removing the source of voltage violation.

6 Acknowledgments

ICT Consilience Creative Program (IITP-2015-R0346-15-1007) supervised by the IITP and under the Basic Science Research Program (NRF-2015R1C1A1A01053788) through the NRF, Korea.

7 References

- [1] Richardson, D.B.: 'Electric vehicles and the electric grid: a review of modeling approaches, impacts, and renewable energy integration', *Renew. Sustain. Energy Rev.*, 2013, **19**, (1), pp. 247–254
- [2] EN 50160: 'Voltage Disturbances Standard', 2011
- [3] Macedo, L.H., Franco, J.F., Rider, M.J., *et al.*: 'Optimal operation of distribution networks considering energy storage devices', *IEEE Trans. Smart Grid*, 2015, **6**, (6), pp. 2825–2836

- [4] Luh, P.B., Yu, Y., Zhang, B., *et al.*: 'Grid integration of intermittent wind generation: A markovian approach', *IEEE Trans. Smart Grid*, 2014, **5**, (2), pp. 732–741
- [5] Murillo-Sanchez, C.E., Zimmerman, R.D., Lindsay Anderson, C., *et al.*: 'Secure planning and operations of systems with stochastic sources, energy storage, and active demand', *IEEE Trans. Smart Grid*, 2013, **4**, (4), pp. 2220–2229
- [6] Jiang, B., Fei, Y.: 'Smart home in smart microgrid: a cost-effective energy ecosystem with intelligent hierarchical agents', *IEEE Trans. Smart Grid*, 2015, **6**, (1), pp. 3–13
- [7] Yang, Z., Wu, R., Yang, J., *et al.*: 'Economical operation of microgrid with various devices via distributed optimization', *IEEE Trans. Smart Grid*, 2016, **7**, (2), pp. 857–867
- [8] Kumar Nanna, H., Doolla, S.: 'Energy management in microgrids using demand response and distributed storage – a multiagent approach', *IEEE Trans. Power Deliv.*, 2013, **28**, (2), pp. 939–947
- [9] Braithwait, S.: 'Behavior modification', *IEEE Power Energy Mag.*, 2010, **8**, (3), pp. 36–45
- [10] Su, W., Wang, J., Roh, J.: 'Stochastic energy scheduling in microgrids with intermittent renewable energy resources', *IEEE Trans. Smart Grid*, 2014, **5**, (4), pp. 1876–1883
- [11] Xiao, H., Huimei, Y., Chen, W., *et al.*: 'A survey of influence of electric vehicle charging on power grid'. Industrial Electronics and Applications (ICIEA), June 2014
- [12] Kuran, M.S., Viana, A.C., Iannone, L., *et al.*: 'A smart parking lot management system for scheduling the recharging of electric vehicles', *IEEE Trans. Smart Grid*, 2015, **6**, (6), pp. 2942–2953
- [13] Dallinger, D., Wietschel, M.: 'Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles', *Renew. Sustain. Energy Rev.*, 2012, **16**, (5), pp. 3370–3382
- [14] Divshali, P.H., Choi, B.J.: 'Electrical market management considering power system constraints in smart distribution grids', *Energies*, 2016, **9**, (6), pp. 1–17
- [15] Kok, K., Widgren, S.: 'A society of devices: integrating intelligent distributed resources with transactive energy', *IEEE Power Energy Mag.*, 2016, **14**, (3), pp. 34–45
- [16] Gridwise Transactive Energy Framework (Version 1.0) (Pacific Northwest National Laboratory (PNNL), Richland, WA, USA, 2015)
- [17] Chang, T.-H., Alizadeh, M., Scaglione, A.: 'Real-time power balancing via decentralized coordinated home energy scheduling', *IEEE Trans. Smart Grid*, 2013, **4**, (3), pp. 1490–1504
- [18] Kirschen, D.S., Strbac, G.: 'Fundamentals of power system economic' (John Wiley & Sons, New York, 2004)
- [19] La, Q.D., Chan, Y.W.E., Soong, B.-H.: 'Power management of intelligent buildings facilitated by smart grid: A market approach', *IEEE Trans. Smart Grid*, 2016, **7**, (3), pp. 1389–1400
- [20] Hasanpor Divshali, P., Choi, B.J.: 'Indirect demand side management program under realtime pricing in smart grids using oligopoly market model'. GREEN 2016, 2016
- [21] Shafie-khah, M., Heydarian-Forushani, E., Osorio, G.J., *et al.*: 'Optimal behavior of electric vehicle parking lots as demand response aggregation agents', *IEEE Trans. Smart Grid*, 2016, **7**, (6), pp. 2654–2665
- [22] Sensfuss, F., Ragwitz, M., Genoese, M.: 'The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany', *Energy Policy*, 2008, **36**, (8), pp. 3086–3094
- [23] Chang, G., Chu, S., Wang, H.: 'An improved backward/forward sweep load flow algorithm for radial distribution systems', *IEEE Trans. Power Syst.*, 2007, **22**, (2), pp. 882–884
- [24] Della Vedova, M.L., Facchinetti, T.: 'Real-time scheduling for peak load reduction in a large set of HVAC loads'. The Third Int. Conf. on Smart Grids, Green Communications and IT Energy-Aware Technologies (ENERGY), Iaria, 2013

- [25] Divshali, P.H., Choi, B.J.: 'Indirect electrical vehicles charging technique based on an imperfect competition market', *IEEE SmartGridComm*, 2016
- [26] Moradzadeh, B., Tomsovic, K.: 'Two-stage residential energy management considering network operational constraints', *IEEE Trans. Smart Grid*, 2013, **4**, (4), pp. 2339–2346
- [27] 'The Operation Data of the Australian Energy Market Operator (AEMO)', Available at http://www.nemweb.com.au/REPORTS/ARCHIVE/Dispatch_SCADA/, accessed June, 2016
- [28] Richardson, I., Thomson, M., Infield, D., *et al.*: 'Domestic electricity use: a high-resolution energy demand model', *Energy Build.*, 2010, **42**, (10), pp. 1878–1887
- [29] 'Domestic Electricity Demand Model – Simulation Example', Available at [https://dspace.lboro.ac.uk/dspace-jspui/handle/2134/5786CREST_Domestic_electricity_demand_model_1.0e\(1\).xlsm](https://dspace.lboro.ac.uk/dspace-jspui/handle/2134/5786CREST_Domestic_electricity_demand_model_1.0e(1).xlsm), accessed June 13, 2016
- [30] Neubauer, J., Brooker, A., Wood, E.: 'Sensitivity of battery electric vehicle economics to drive patterns, vehicle range, and charge strategies', *J. Power Sources*, 2012, **209**, (1), pp. 269–277
- [31] 'Smartgridcity Pricing Plan Comparison Chart', <http://smartgridcity.xcelenergy.com/media/pdf/SGC-pricing-plan-chart.pdf>, accessed Jun 13, 2016
- [32] Yao, E., Samadi, P., Wong, V.W., *et al.*: 'Residential demand side management under high penetration of rooftop photovoltaic units', *IEEE Trans. Smart Grid*, 2016, **7**, (3), pp. 1597–1608

8 Appendix

Theorem: Algorithm 4 converges to the equilibrium of the market.

Proof: In a rational market, the following assumption are always true: (i) Supply curve (S) is a non-decreasing function, (ii) demand curve (D) is a non-increasing function, (iii) the initial cost of production ($S(0)$) is less than the price that customers would be willing to pay for the first unit of production ($D(0)$), and (iv) demand curve always has positive value, so $D(\infty) \geq 0$ and $S(\infty) \rightarrow \infty$. In these circumstances, the function (F), which is defined as $F = D - S$ is a non-increasing function whose root is the market equilibrium (RTP). Since $F(0) > 0$ and $F(\infty) < 0$, the bisecting method can find the root of F . Therefore, Algorithm 4, which is bisecting the difference of supply and demand curve, converges to the market equilibrium.