Distributed Optimal Co-multi-microgrids Energy Management for Energy Internet

Bonan Huang, Yushuai Li, Huaguang Zhang, *Fellow, IEEE*, and Qiuye Sun, *Member, IEEE*

***Abstract*—Unlike conventional power systems, the upcoming energy internet (EI) emphasizes comprehensive utilization of energy in the whole power system by coordinating multi-microgrids, which also brings new challenge for the energy management. To address this issue, this paper proposes a novel consensus-based distributed approach based on multi-agent framework to solve the energy management problem of the energy internet, which only requires local information exchange among neighboring agents. Correspondingly, two consensus algorithms are presented, one of which drives the incremental cost of each distributed generator (DG) converge to the state of the leader agent-energy router, and the other one is used to estimate the global power mismatch, which is a first-order average consensus algorithm modified by a correction term. In addition, in order to meet the supply-demand balance, an effective control strategy for the energy router is proposed to accurately calculate the power exchange between the microgrid and the main grid. Finally, simulation results within a 7-bus test system are provided to illustrate the effectiveness of the proposed approach.**

***Index Terms*—Consensus, multi-agent, energy management, optimization, energy internet.**

I. INTRODUCTION

WITH the deterioration of natural environment and the aggravation of global energy crisis, considerable attention has been paid to the study of improving energy efficiency, increasing economical efficiency, integrating high penetration of renewable energy and decreasing carbon emission in the past decades. As a promising way to solve these problems, the concept of energy internet (EI) was developed in recent years[1−2]. However, the future power-grid based on EI framework also brings new challenges to the study of some basic problems in power systems, one of which is the problem of energy management.

In recent years, numerous algorithms have been reported for the energy management of traditional power systems, which include analytical methods such as Lagrange multipliers[3], gradient search methods, the linear programming, the Newton's approach[4] and heuristic methods such as the genetic algorithm[5] and the particle swarm algorithm, etc. Note that, most of these methods are performed in a centralized way and deployed at large timescale. However, with the transformation from traditional power systems to EI, traditional centralized methods may encounter the following problems in application of energy management:

1) The centralized approaches require high-bandwidth communication infrastructure to gather global information from every single system component and a central controller with high computational ability to process a huge mass of data, which will result in not only great implementation cost but also high sensitivity to single-point failures and modeling errors.

2) Both the physical and communication topologies of EI tend to subject to topology variability due to the plug-and-play feature of system components in EI, which may seriously undermine the efficacy of the centralized approaches.

Alternatively, the distributed approach which does not rely on a central controller could be more applicable to deal with the topology variability and the plug-and-play feature. Moreover, it possesses more robustness, scalability and can be better operated under limited-bandwidth communication[6]. Therefore, it is a promising way to solve the energy management problem of EI by proper distributed approaches. Consensus-based distributed approaches have been widely studied to solve practical engineering problems in recent years, in which each agent only requires the information exchanging among its neighbor agents through a local communication network to find the optimal solutions[7−8]. As for the energy management problem, there are also fruitful results reported in existing literatures. For instance, the quadratic convex cost function was used to analyze the energy management problem with or without a leader in [9 − 11], where the estimated power mismatch was used as a feedback mechanism to meet the supply-demand balance constraint. The transmission line losses along with generator constraints were taken into account in [12], which was based on two consensus protocols running in parallel to find the optimal solution. Considering the ramping rate limits, a distributed approach based on the dynamic programming algorithm was proposed in [13], with simpler implementation and faster convergence speed. Taking the demand response into consideration, the authors in [14 − 16] focused on maximizing the total social welfare by combining the suppliers' generations and customers' demand. In addition, the problems of online optimal generation control, self-organizing and non-convex dispatch model were discussed in [17 − 19].

It is worth noting that all aforementioned distributed energy management approaches are restricted in the islanded mode,

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aiming at achieving the optimal synthetical cost in a single but not at the whole power system. However, the future EI emphasizes the comprehensive utilization of energy in the whole power system by coordinating multi-microgrids and minimizing the cost of the whole power system, but not only the energy of any single microgrid, which inevitably results in a certain amount of power exchange among the microgrids. In other words, each microgrid can either inject spare power (if working in low loads) into or absorb lacking power (if working in high loads) from other microgrids or the main grid. Therefore, how to accurately calculate the exchange power among microgrids and the power outputs of DGs in a distributed fashion is urgent for the energy management of the forthcoming EI. To address this issue, this paper proposes a novel distributed approach to solve the energy management problem of EI by considering the power exchange among multi-microgrids and the main grid. The proposed approach is based on two consensus algorithms, one of which requires a leader agent to drive the incremental cost of each DG to the set electricity price, and the other one modified by a correction term is used to estimate the power mismatch between the load demand and the total power generation. In addition, a novel control strategy for the energy router is proposed to calculate the value of power exchange. The major contributions of the proposed distributed approach are summarized as follows:

1) The proposed approach is implemented in a distributed fashion, which only requires local communication among neighbors. Thus, it is more cost-effective, reliable and robust compared to the centralized approaches.

2) The proposed approach can achieve the co-optimization among microgrids, which can effectively improve the energy efficiency and the economic benefit.

3) Various kinds of distributed generators are considered in the system modeling to further achieve their integrated optimization and the local consumption of DGs.

Finally, simulation results under different cases in a test system are provided to illustrate the satisfactory performance of the proposed approach.

The rest of this paper is summarized as follows. Section II introduces the structure of EI and the mathematical model of the concerned energy management problem. Section III introduces the graph theory and the proposed distributed approach. Section IV provides some case studies to verify the effectiveness of the proposed approach. Finally, Section V concludes this paper.

A typical structure of EI contains multi-microgrids and the main grid (MG), shown in Fig. 1. In such EI structure, each microgrid is connected to the MG by an energy router which can obtain the electricity price from the MG and ensures constant power exchange between the MG and the microgrid[2]. In each microgrid, the energy resources consist of the MG and various kinds of DGs which include distributed conventional fuel generators and distributed renewable generators (e.g. photovoltaics (PVs) and wind turbines (WTs). Letting m and N represent the numbers of microgrids and DGs for each microgrid, respectively, then the power supply-demand balance considering the electricity price can be formulated as follows:

$$\sum_{i=1}^{N} p_i + p_{MG} = D_L, \tag{1}$$

where p_i is the power generated by the ith DG, D_L is the total load demand and p_{MG} is the power exchange between the microgrid and the MG. Therein, if the microgrid injects power into the MG, then $p_{MG} < 0$; if the microgrid absorbs power from the MG, then $p_{MG} > 0$; otherwise, $p_{MG} = 0$.

The cost function of DGs is usually approximated by the following quadratic convex function:

$$C_i\left(p_i\right) = a_i p_i^2 + b_i p_i + c_i, \tag{2}$$

$$p_i^{\min} < p_i < p_i^{\max}, \tag{3}$$

where a_i, b_i, c_i are the cost coefficients, $p_i^{\min}$ and $p_i^{\max}$ are the lower and upper bounds of the power generated by the generator i, respectively. It is worth noting that $p_i^{\max}$ is the value of maximum power point tracking (MPPT) point for the distributed renewable generator i. In addition, the incremental cost[12−13] of each DG is defined as:

$$\frac{\partial C_i\left(p_i\right)}{\partial p_i} = 2a_i p_i + b_i. \tag{4}$$

The energy management of each microgrid aims at finding a suitable power generation combination of all DGs and the power exchange between the microgrid and the MG, which gives the minimum economical cost while satisfies the system supply-demand balance and various inequality constraints. Therefore, the energy management problem can be mathematically represented as follows:

$$\operatorname{Min} \sum_{i}^{N} C_i\left(p_i\right) + \kappa p_{MG}, \tag{5}$$

which subjects to constraints (1), (3) and κ is the electricity price. And it is easy to see that the total goal of the whole system is the aggregate goal of all microgrids.

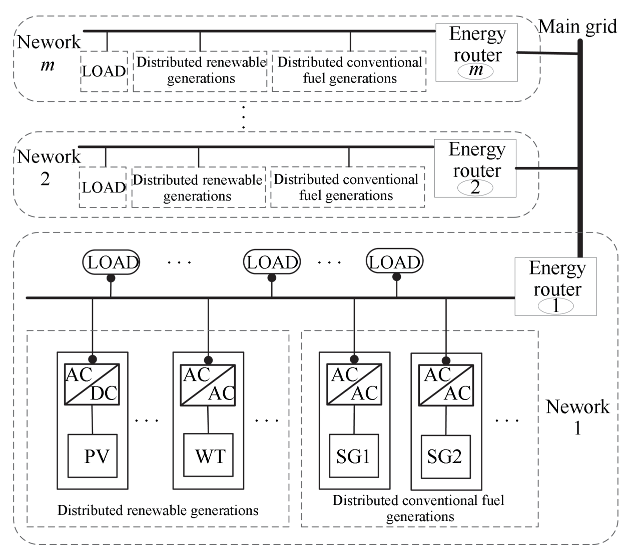

Fig. 1. The structure of energy internet.

A. Optimal Conditions Analysis

In this part, we will analyze the optimal conditions of this kind of optimization problem and further provide its distributed solution strategy in Section III.

It is easy to have the Lagrangian function of (5), that is:

$$\begin{aligned} L = \sum_{i}^{N} C_i\left(p_i\right) + \kappa p_{MG} - \lambda\left(\sum_{i=1}^{N} p_i + p_{MG} - D_L\right) \\ - \sum_{i=1}^{N} \mu_i^{\min}\left(p_i - p_i^{\min}\right) - \sum_{i=1}^{N} \mu_i^{\max}\left(p_i^{\max} - p_i\right), \end{aligned} \tag{6}$$

where λ, $\mu_i^{\min}$, $\mu_i^{\max}$ are the Lagrangian multipliers of the equality constraint (1) and the inequality constraints (3) for each DG, respectively.

Without considering the inequality constraints, the optimal conditions of (6) are given by:

$$\begin{cases} \dfrac{\partial L}{\partial p_i} = 2a_i p_i + b_i - \lambda = 0, \\ \dfrac{\partial L}{\partial p_{MG}} = \kappa - \lambda = 0. \end{cases} \tag{7}$$

From (7), the necessary conditions for the existence of the optimal operating point is that the incremental cost of each DG is equal to λ, meanwhile $\lambda = \kappa$. When each DG is running in the optimal configuration, the power generation $p_i{}^*$ and the electricity price κ should satisfy the following conditions:

$$\begin{cases} p_i^* = \dfrac{(\lambda - b_i)}{2a_i}, \\ \lambda = \kappa. \end{cases} \tag{8}$$

Then, from (1), the optimal exchanged power can be obtained by

$$p_{MG}^* = D_L - \sum_{i=1}^{N} p_i^*. \tag{9}$$

Above analysis shows that to achieve the optimal solutions of problem (5) with its corresponding equality constraint (1), all DGs in microgrids should hold the same incremental cost which is equal to electricity price κ. Meanwhile, suitable exchanged power for each energy router needs to be calculated to maintain their corresponding supply-demand balance. It should be noted that the sign of the calculated p_{MG}^* , which could be plus or minus, implies the microgrid would inject power into or absorb power from the MG, and the value of $\mid p_{MG}^* \mid$ means the quantity of the power need to be exchanged. To be more specific, in the scenario of co-multi-microgrids, there are always some microgrids running in the low-load condition or in the high-load condition and it is expected that they can cooperatively achieve the optimal energy management of the whole system. The same incremental cost makes the cooperation possible by making the microgrids in the low-load condition generate more power into MG to feed the ones in the high-load condition. Meanwhile the microgrids in the high-load condition can absorb power with lower cost from the MG to compensate the part of power with higher cost. Therefore, if the incremental cost of each DG can converge to κ and the energy router can calculate the optimal exchanged power p_{MG}^*, then the optimal energy management of the whole system can be achieved.

When taking the inequality constraints into consideration, we only need to extend the optimal conditions for p_i to the following form:

$$\begin{cases} 2a_i p_i + b_i = \lambda, & p_i^{\min} < p_i < p_i^{\max}; \\ 2a_i p_i + b_i \le \lambda, & p_i = p_i^{\max}; \\ 2a_i p_i + b_i \ge \lambda, & p_i = p_i^{\min}. \end{cases} \tag{10}$$

II. DISTRIBUTED OPTIMAL ENERGY MANAGEMENT

A. Graph Theory

Considering a microgrid with one energy router and N DGs, a graph $\mathcal{G}=\{0\} \cup G$ is used to model the network topology of the system and the way that system elements exchange information based on the communication infrastructure. Therein, $\{0\}$ represents the energy router and G is a weighted graph which is defined as $G\left(V, E, W\right)$, where $V = \left(v_1, v_2, \ldots, v_n\right)$ is a set of elements called nodes, $E = \{e_{ij} = (v_i, v_j)\} \subset V \times V$ is a set of pairs of distinct nodes called edges and $W = (w_{ij}) \in \mathbf{R}^{N\times N}$ is the associated adjacency matrix. Graph nodes represent the DGs, the edges represent the transmission lines among DGs, and the adjacency matrix reflects the edge weights which describe the degree of the interaction effect between nodes. If there exists an edge e_{ij} from DG j to DG i with $w_{ij} > 0$, then DG j is called a neighbor of DG i, which means DG i can receive information from DG j. The set of neighbors of DG i is denoted by $\mathcal{N}_i$ with cardinality w_i. Define $D = \operatorname{diag}\{d_1, d_2, \ldots, d_N\}$ as the leader adjacency matrix associated with $\mathcal{G}$, in which we have $d_i > 0$ if DG i can receive information from the energy router; otherwise, $d_i = 0$. And the set of DGs with $d_i > 0$ is denoted by $\mathcal{N}_0$ with cardinality w_0. In real power systems, it is always expected to achieve the systems function with communication lines as few as possible. Therefore, we let only a small percentage of DGs have $d_i > 0$, i.e., only a small percentage of DGs can receive information from the energy router. In addition, let G be a strongly connected graph, then $\mathcal{G}$ contains a directed spanning tree and $\{0\}$ is the root[22].

B. Distributed Approach

According to the analysis in the previous section, the incremental cost of each DG must converge to κ when it runs at the optimal operating point. This operation can be performed by using the leader-following consensus algorithm, meanwhile let the energy router be the leader, which can obtain the electricity price from the MG and locally exchange information with its neighbors. Then, each DG updates its incremental cost by running the following protocol:

$$\lambda_i\left(k+1\right) = \sum_{j\in\mathcal{N}_i} w_{ij}\lambda_j\left(k\right) + d_i\lambda_0\left(k\right), \tag{11}$$

where $\lambda_i\left(k\right)$ represents the estimated incremental cost of DG i, $\lambda_0\left(k\right)$ which is equal to κ, denotes the state of the leader agent. According to the leader-following consensus algorithm[20], if $\sum_{j\in\mathcal{N}_i} w_{ij} + d_i = 1$, then all the estimated incremental costs of DGs will synchronize to the state of the leader, i.e., $\lim_{k\to\infty}\left\|\lambda_i\left(k\right) - \kappa\right\| = 0$. Furthermore, each

DG locally updates its power generation while meeting the following inequality constraints:

$$p_i(k+1)=\begin{cases} p_i^{\min}, & \text{if } \frac{\lambda_i(k+1)-b_i}{2a_i}<p_i^{\min};\\ \frac{\lambda_i(k+1)-b_i}{2a_i}, & \text{if } p_i^{\min}\leq\frac{\lambda_i(k+1)-b_i}{2a_i}\leq p_i^{\max};\\ p_i^{\max}, & \text{if } \frac{\lambda_i(k+1)-b_i}{2a_i}>p_i^{\max}.\end{cases} \tag{12}$$

Based on (11), (12), the optimal power generations of the DGs can be obtained. That is, each DG increases (or decreases) its incremental cost and generates more (or less) power when its corresponding incremental cost is higher (or lower) than κ. Then, the incremental cost of each DG will synchronize to the electricity price after a sufficient long time K. In order to calculate the power exchange between the microgrid and MG while satisfying the power supply-demand balance constraint (1), the updating rules of the power mismatch among all DGs and the control strategy for energy router are defined as follows:

$$y_i(k+1)=\sum_{j\in\mathcal{N}_i}\bar{w}_{ij}y_j(k)+p_i(k)-p_i(k+1), \tag{13}$$

$$p_{MG}(k+1)=\frac{N}{w_0}\sum_{j\in\mathcal{N}_0}y_j(k+1), \tag{14}$$

where $y_i(k)$ is the estimated power mismatch and $\bar{W}=(\bar{w}_{ij})\in\mathbf{R}^{N\times N}$ is doubly stochastic. In this paper, we assume that each node has its own unique identity (ID). Then, the nodes number N can be obtained in a distributed fashion by employing the message marking method[12].

Based on (13), (14) along with (11), (12), $p_{MG}(k)$ can converge to $\sum_{i=1}^{N}p_i(k+1)-D_L$, as $k\to\infty$, $\forall i\in V$.

Proof. Firstly, define the following initializations:

$$\begin{aligned} &p_i(0)=\begin{cases} p_i^{\min}(0), & D_i\leq p_i^{\min}(0),\\ p_i(0), & p_i^{\min}(0)\leq D_i\leq p_i^{\max}(0),\\ p_i^{\max}(0), & p_i^{\max}(0)\leq D_i,\end{cases}\\ &\lambda_i(0)=0,\\ &y_i(0)=D_i-p_i(0),\end{aligned} \tag{15}$$

where D_i is the load demand associated with DG i at bus i. If there are only loads at bus i, let $p_i^{\min}=p_i^{\max}=0$. In this initializations, it can be obtained that $\sum_{i=1}^{N}y_i(0)=\sum_{i=1}^{N}D_i-\sum_{i=1}^{N}p_i(0)=D_L-\sum_{i=1}^{N}p_i(0)$.

Secondly, due to $\bar{W}$ is a doubly stochastic matrix, it is not hard to verify that

$$\begin{aligned} &\sum_{i=1}^{N}y_i(k+1)+\sum_{i=1}^{N}p_i(k+1)=\sum_{i=1}^{N}y_i(k)+\sum_{i=1}^{N}p_i(k)\\ &\quad=\sum_{i=1}^{N}y_i(0)+\sum_{i=1}^{N}p_i(0)=D_L\\ &\quad\to\sum_{i=1}^{N}y_i(k+1)=D_L-\sum_{i=1}^{N}p_i(k+1).\end{aligned} \tag{16}$$

Furthermore, based on the analysis of (11) and (12), $p_i(k+1)=p_i(k)$ is always satisfied for $k>K$. Thus, (13) forms the first-order average consensus protocol[21] for $k>K$. Then for $k\to\infty$, all of the estimated power mismatches of DGs converge to a constant C, i.e., $\lim_{k\to\infty}y_i(k+1)=C$. Therefore, we get:

$$\begin{aligned} &\sum_{i=1}^{N}y_i(k+1)=NC=D_L-\sum_{i=1}^{N}p_i(k+1)\\ &\quad\Rightarrow y_i(k+1)=\left(D_L-\sum_{i=1}^{N}p_i(k+1)\right)/N.\end{aligned} \tag{17}$$

Lastly, along with (14) and (17), for $k\to\infty$, we get:

$$\begin{aligned} p_{MG}(k+1)&=\frac{N}{w_0}\sum_{j\in\mathcal{N}_0}y_j(k+1)\\ &=\frac{N}{w_0}\left(w_0\left(D_L-\sum_{i=1}^{N}p_i(k+1)\right)/N\right)\\ &\Rightarrow p_{MG}(k+1)+\sum_{i=1}^{N}p_i(k+1)-D_L=0.\end{aligned} \tag{18}$$

Note that equations (11) to (14) constitute the distributed approach, in which each component only requires local communication with its neighbors. And theoretical analysis shows that the proposed approach can effectively solve the energy management problem of EI and all variables can converge to the optimal solution, i.e.,

$$\lambda_i(k)\to\kappa, p_i(k)\to p_i^*, p_{MG}(k)\to p_{MG}^*, \text{as } k\to\infty, \forall i\in V.$$

Remark 1. It should be noted that if we use a centralized method to solve the energy management problem, we can directly set $\lambda_i=\kappa$ via a central controller and a two-way communication network between the central controller and all DGs, and then the optimal generated and exchanged power can be obtained by (10) and (9). However, this paper focuses on solving the energy management problem in a distributed fashion within the multi-agent framework, which does not rely on a central controller and high-cost full-communication network. Each DG only knows its neighbors' information through a local network and only the energy router can get the electricity price information κ from the MG. Therefore, the $\lambda_i=\kappa$ of each DG is expected to synchronize to the electricity price state of the energy router by iteration based on the consensus protocol to make all $\lambda_i\to\kappa$.

III. Simulation Results

In this section, several case studies are provided to verify the effectiveness of the proposed approach. The first case study shows the performance of the proposed approach in an EI test system. The second case demonstrates the capability of the proposed approach under time-varying electricity price condition. The third and fourth case studies show the plug-and-play adaptability and the performance to accommodate the time-varying demand of the proposed approach, respectively. The EI test systems, as shown in Fig. 2, contains five DGs, one energy router, and the communication topology dependent on the physical structure. The characteristics of each DG are given in Table I, and the system initialization is based on (15).

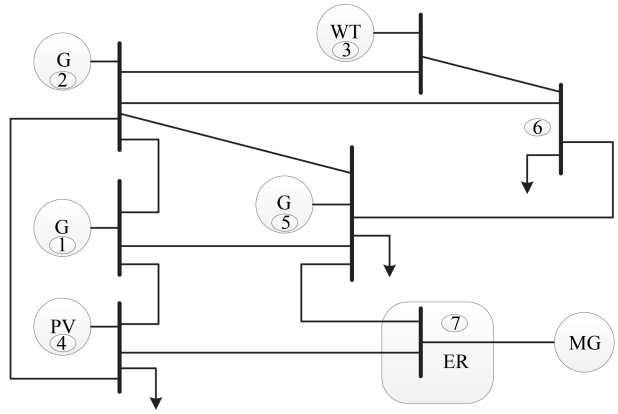

Fig. 2. Configuration of the energy internet test system.

TABLE I
PARAMETERS OF THE TEST SYSTEM

DG Type	a	b	c	$p_i^{\min}$	$p_i^{\max}$
G1	0.00533	11.669	213.1	50	200
G2	0.00889	10.333	200	37.5	150
WT3	0.00001	0.5000	10	0	80
PV4	0.00005	0.2000	15	0	100
G5	0.00741	10.833	240	45	180

A. Case Study 1: Performance of the Proposed Approach

In this case study, the total demand is 450 (p. u.) with three loads of 150 (p. u.), and the electricity price is 12 (p. u.). The update of the incremental costs, the power generated by DGs and the exchange power by energy router, the total generation and the exchange power are shown in Figs. 3-5, respectively. It can be observed that all the incremental costs of DGs are increased and finally converged to the common value 12 (p. u.). Moreover, the sum of the total generation and exchange power is equal to the total load demand, which means the supply-demand balance constraint in EI is satisfied. Moreover, the generation and exchange power are $p_1 = 50.0000$ (p. u.), $p_2 = 93.7271$ (p. u.), $p_3 = 80.0000$ (p. u.), $p_4 = 100.0000$ (p. u.), $p_5 = 78.7173$ (p. u.), and $p_{MG} = 47.5548$ (p. u.), which means that the final estimated generated power by each DG is within its corresponding lower and upper bound. Therefore, the optimality objective is achieved. It should be noted that $p_{MG} > 0$ implies the network should absorb 47.5548 (p. u.) power from the MG with lower cost. That is, the total generation power of the DGs is less than the total load demand when all the incremental costs achieve the leader state

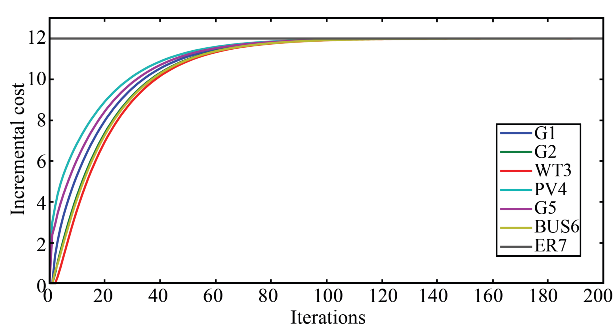

Fig. 3. Incremental cost update in Case 1.

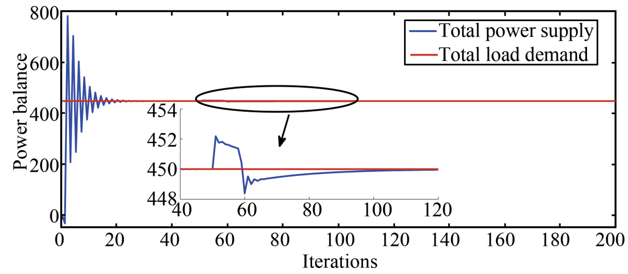

Fig. 4. Power balance in Case 1.

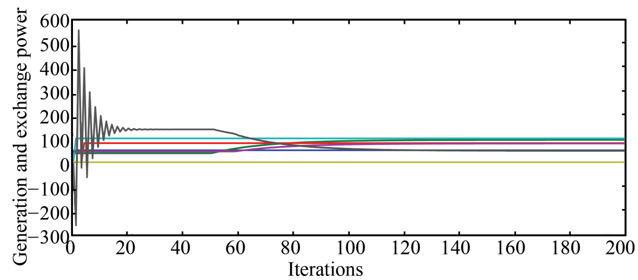

Fig. 5. Generation and exchange power update in Case 1.

(12 (p. u.)). Moreover, if the remaining loads are still supplied by the DGs, then the incremental cost will increase, resulting in higher cost. On the contrary, if the remaining loads are supplied by the MG, then they can obtain the lacking power in invariant unit electricity price with lower cost than the former.

B. Case Study 2: Time-varying Electricity Price Condition

This case focuses on studying the performance of proposed approach under the time-varying electricity price condition. In this case study, the electricity price has been changed twice: 1) at time step $k = 201$, the electricity price increases to 13 (p. u.); 2) at time step $k = 401$, the electricity price reduces to 11.5 (p. u.). From the results shown in Fig. 6-8, it can be seen that all the incremental costs, generation, and exchange power automatically converge to new solutions, meanwhile the sum of the total generation and exchange power can meet the supply-demand balance constraint under every electricity price change. Based on the results at $k = 400$, i.e., $\lambda = 13$ (p. u.), $p_1 = 124.8555$ (p. u.), $p_1 = 124.8555$ (p. u.), $p_2 = 149.9974$ (p. u.), $p_3 = 80.0000$ (p. u.), $p_4 = 100.0000$ (p. u.), $p_5 = 146.2189$ (p. u.) and $p_{MG} = -151.0717$ (p. u.), it can be seen that the incremental cost of each DG is increased and synchronized to the leader state, which results in more power generation. Notice that $p_{MG} < 0$, which means the network will inject 151.0717 (p. u.) power into the MG. Moveover, the unit cost of that part of power, i.e., the incremental cost, is lower than the electricity price (13 (p. u.)), which makes additional profit by selling that power to the MG. In addition, based on the results at $k = 600$, i.e., $\lambda = 11.5$ (p. u.), $p_1 = 50.0000$ (p. u.), $p_2 = 65.6393$ (p. u.), $p_3 = 80.0000$ (p. u.), $p_4 = 100.0000$ (p. u.), $p_5 = 45.0102$ (p. u.) and $p_{MG} = 109.3506$ (p. u.), it implies that DGs have to reduce their power outputs to accommodate the new lower electricity price. Therefore, the case study shows that the proposed approach can effectively accommodate the time-varying electricity price condition.

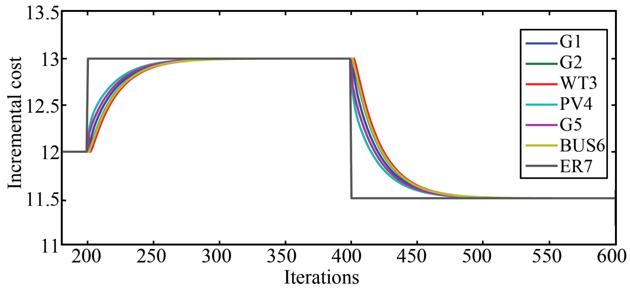

Fig. 6. Incremental cost update in Case 2.

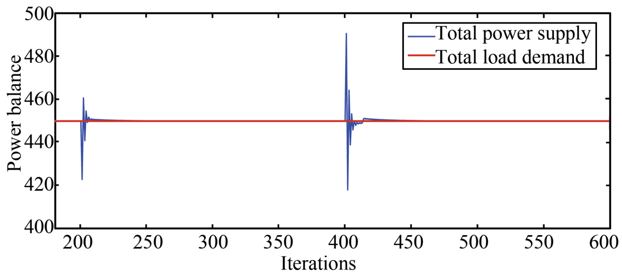

Fig. 7. Power balance in Case 2.

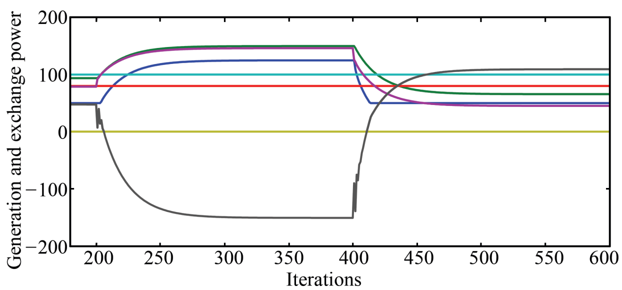

Fig. 8. Generation and exchange power update in Case 2.

C. Case Study 3: Plug-and-play Capability

The case study focuses on testing the plug and play adaptability of the proposed approach. At time step $k = 201$, DG1 is disconnected from the test system, and all of the variables of DG1 are set to zero. From the results shown in Fig. 9, the incremental costs of the remaining DGs which remain unchanged due to the invariant electricity price, make the corresponding power outputs constant. As a result, the network has to further absorb 50 units power from the MG to compensate the power perviously supplied by DG1 as is shown in Fig. 11. Meanwhile, the sum of total generation and exchange power can also converge to the total load demand. At time step $k = 201$, DG1 is plugged in again. Then, let the outputs of DG1 be set to $p_1(201) = 50.0000$ (p. u.), $y_1(201) = 0$ (p. u.) and $\lambda_1(201) = 0$ (p. u.), it can be seen

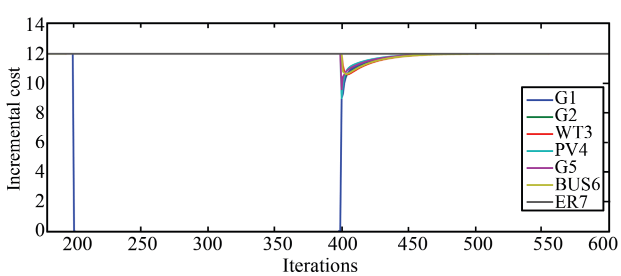

Fig. 9. Incremental cost update in Case 3.

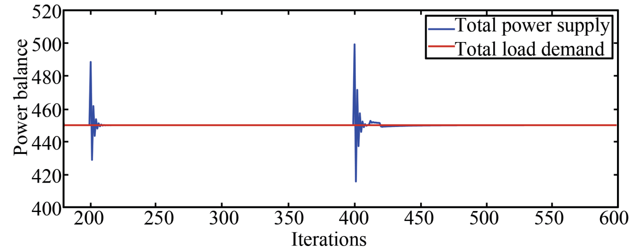

Fig. 10. Power balance in Case 3.

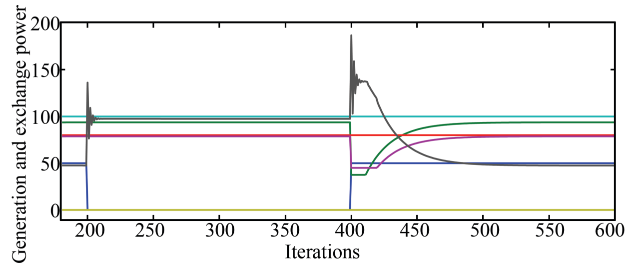

Fig. 11. Generation and exchange power update in Case 3.

that the system converges to new optimal solutions to adapt to the new topological change, in which the solutions are the same as the ones before DG1's disconnection. Therefore, this case study shows that the proposed approach can effectively adapt to the plug-and-play feature of EI.

D. Case Study 4: Time-varying Load Condition

This case study focuses on studying the performance of the proposed approach to accommodate the time-varying demand. At time step $k = 201$, the system load demand increased by 20 % makes the total load demand increase to 540 (p. u.). From the results shown in Figs. 12-14., the system automatically responds to the loading change and converges to a new solution. Due to invariant electricity price, the incremental cost of each DG which remains unchanged during the load change, makes the corresponding power outputs constant. Then the network has to absorb 90 units power from the MG, which

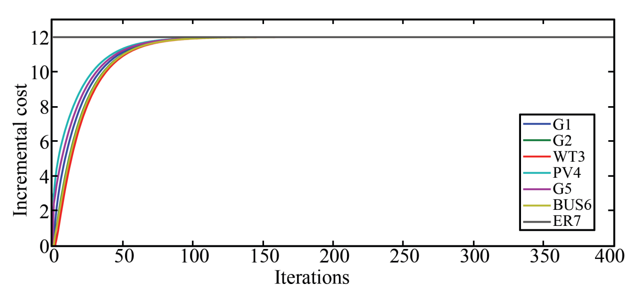

Fig. 12. Incremental cost update in Case 4.

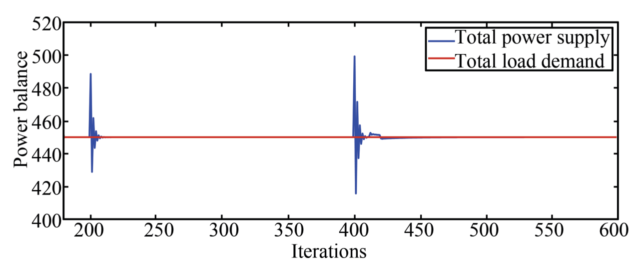

Fig. 13. Power balance in Case 4.

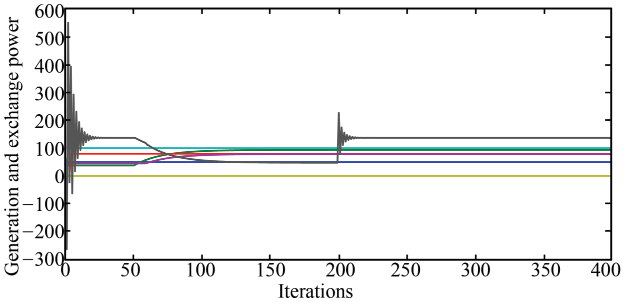

Fig. 14. Generation and exchange power update in Case 4.

makes the $p_{MG}(400)$ increase to 97.5548 (p. u.) to meet the increased load demand. Therefore, simulation results show that the proposed approach can effectively accommodate the time-varying load condition.

IV. CONCLUSION

This paper proposes a novel distributed approach to solve the energy management problem of EI, whose solution is obtained by the agents network via exchanging and processing local information according to consensus-based protocols. All of the incremental cost of DGs can converge to the leader's state by using the leader-following consensus strategy, and each DG can locally estimate the global power mismatch by using the modified average consensus strategy. In addition, the paper also proposes an effective control strategy for the energy router to calculate the values of power exchange. Simulation results obtained on a 7-bus EI test system demonstrate the effectiveness of the proposed approach.

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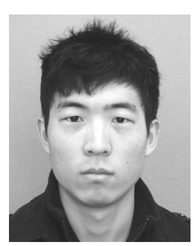

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