Distributed Power Dispatching Solution for A Future Economic and Environment-friendly Energy Internet

Yang Li
Big Data Center of State Grid
Corporation of China,
Beijing, P. R. China

Zhaoming Qin
Beijing National Research Center for
Information Science and Technology,
Tsinghua University
Beijing, P. R. China

Fan Zhang
Big Data Center of State Grid
Corporation of China,
Beijing, P. R. China

Yuchao Qin
Beijing National Research Center for
Information Science and Technology,
Tsinghua University
Beijing, P. R. China

Haochen Hua*
Beijing National Research Center for
Information Science and Technology,
Tsinghua University
Beijing, P. R. China

Junwei Cao
Beijing National Research Center for
Information Science and Technology,
Tsinghua University
Beijing, P. R. China

ABSTRACT

In recent years, the research of power dispatch has been popular in the field of energy Internet (EI) system operation and management. In this paper, a distributed algorithm considering multiple objectives is applied to solve power dispatch problem within the scenario of energy Internet. The power dispatch problem is formulated as a convex optimization problem, and subgradient-push distributed strategy is designed for each agent. In this manner, the decentralized scheme can be more suitable for the power dispatch of large multi-agent network. Case study is performed to validate the feasibility of the proposed method.

KEYWORDS

Convex optimization, distributed algorithm, energy Internet, power dispatch

1 INTRODUCTION

The concept of energy Internet (EI) has been popular during the past five years, since it was proposed by Rifkin [1]. Among all the research subjects within the field of EI, power dispatch issue has always been regarded as a significant topic [2], [3]. One of the main factors affecting power distribution is economy; see, e.g., [4], [5]. However, with the enhancement of public awareness of environmental protection and the formation of international consensus on atmospheric protection (such as the Paris Accord adopted at the Paris Climate Conference in 2015), environmental factors have been gradually taken into account in power dispatch. For example, environmental and economic power dispatch has been investigated in [6].

In the field of power systems, the centralized control algorithm has been widely developed over the last decades. In [7] and [8], the centralized H_∞ method has been proposed to ensure EI system frequency stability. In [9], a model predictive control strategy is proposed to solve power dispatch in energy Internet. To ensure DC microgrids' voltage stability, centralized robust control strategy has been proposed in [10]. To check and schedule energy router system, a probabilistic model is presented in [11]. When operation cost is mainly considered to be minimized, a stochastic optimal control scheme has been designed to achieve such target in EI [12]. When both system robustness and operation cost optimization are considered in EI, readers can refer to [13], [14], etc.

In a centralized method, all agents have to transmit their information to the central controller, which may undermine privacy and stealth. Moreover, with a large multi-agent network, the centralized method faces severe challenges such as computational burden. The system stability is also a worrying issue, especially when single point of failure occurs frequently. For the detailed advantage of decentralized control over centralized control, readers can refer to [15] and the references therein. In this sense, distributed method has attracted more attention.

The literature review also confirms a growing interest in decentralized algorithm in the field of EI systems. A distributed method for economic dispatch considering random wind power is proposed in [16]. A consensus-based algorithm for economic dispatch is discussed in [15], while energy storage is not considered. A multiagent-based consensus algorithm is applied for coordinated control of distributed generators in [17]. To deal with different energy forms and diversified energy roles, a distributed energy management framework is presented in [18]. A distributed bisection method for economic power dispatch is studied in [19]. To solve optimal power flow problem with demand response, a decentralized consensus-based ADMM Approach is proposed in [20]. A distributed algorithm over time-varing directed networks with delays is investigated in [21]. Nevertheless, environmental effect of emission is not considered in the aforementioned works.

In this paper, the optimal power dispatching problem in an EI system is investigated. The economic and environmentally friendly operation of the whole system is firstly formulated as a convex optimization problem. By utilizing an advanced distributed optimization approach, the investigated optimization problem is solved in a decentralized fashion effectively. The results are compared with conventional methods in the case study, and the performances of different dispatching schemes are analyzed in detail to illustrate the effects of different weighting factor settings for the objective function.

---

*Corresponding author: Haochen Hua, hhua@tsinghua.edu.cn.

The main contributions of this paper can be found as follows:

- Three performance indexes, the economic operation cost of controllable power generators, the environmental impact from pollutant emission of generators as well as the rational utilization of energy storage devices, are addressed simultaneously in a typical EI scenario.
- An advanced distributed optimization algorithm named *subgradient-push* [22] is adopted in this paper to find solution for the corresponding optimization problem, which needs no knowledge of the graph for each agent, except the number of its neighbourhood.
- The design of the power dispatching scheme proposed in this paper allows a variety of applications in the future EI systems. With different settings of weighting coefficients, the importance of the three performance indexes could be properly taken into consideration. The feasibility and effectiveness of power dispatching schemes with different parameter settings are evaluated with real-world grid data. A detailed analysis regarding settings of weighting factors are presented in the case study section of this paper.

The rest of this paper is organized as follows. In Section 2, the physical power model and topological structure of EI is introduced. Then, power dispatch is formulated as a convex optimization problem in Section 2.1, and the algorithm for solving such problem is provided in Section 3. The feasibility of the distributed method is verified in Section 4. Finally, conclusion is given in Section 5.

2 SYSTEM DESCRIPTION

In this paper, an typical EI system with N subgrid is investigated. Without loss of generality, each of the subgrid is assumed to be composed of residential loads, battery energy storage systems, uncontrollable power generators, e.g., distributed photovoltaic generators and wind turbines, and controllable power generators such as diesel engine generators, fuel cells and micro turbines. These individual subgrids in the considered EI system are interconnected via the local power transmission network. A typical EI system investigated in this paper is illustrated in Fig. 1.

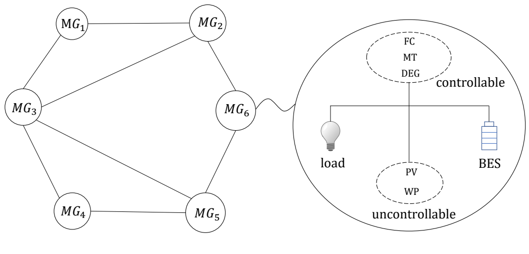

Figure 1: An EI system consisting of 6 microgrids.

2.1 Problem Formulation

The structure of the local power transmission network is represented by an undirected graph denoted as $\mathcal{G}(\mathcal{V},\xi)$. Here, $\mathcal{V}$=$\{1,2,\ldots,N\}$ is the set of subgrids with cardinality $|\mathcal{V}|$=N, and $\xi \subseteq \mathcal{V}\times\mathcal{V}$ represents connectivity among subgrids with $|\xi|$=M. In order to share information among subgrids and achieve the dispatching of power generation, a smart agent is deployed to each generator. If an agent j can exchange information with agent i, the agent j is considered as a neighbour of agent i, and the neighbourhood of the agent i is denoted as $\mathcal{N}_i$=$\{j\in\mathcal{V} \mid (i,j)\in\xi\}$ with $|\mathcal{N}_i|$=d_i.

For a given time t, we denote the controllable generator in the i-th subgrid as G_i, and its power generation is denoted by P_i^G. The generation capacity constraints for G_i are given by

$$P^G_{min,i} \le P^G_i \le P^G_{max,i}, \tag{1}$$

where, $P^G_{min,i}$ and $P^G_{max,i}$ are the minimum and maximum power of G_i, respectively.

As the complement of generators, the battery energy storage are deployed in the subgrids such that the drastic power deviation from the residential loads and uncontrollable power generators could be properly absorbed. Let us denote the battery in the i-th subgrid as B_i. The charge/discharge power and state of charge (SOC) of B_i are denoted as P_i^B and SOC_i, respectively. The restrictions for P_i^B are given by

$$P^B_{min,i} \le P^B_i \le P^B_{max,i}. \tag{2}$$

In (2), $P^B_{min,i}$ and $P^B_{max,i}$ are defined as

$$P^B_{min,i} = \begin{cases} -P^{Bc}_{max,i}, & when \quad SOC_i \ge SOC_{min,i} \\ 0, & when \quad SOC_i < SOC_{min,i} \end{cases},$$

$$P^B_{max,i} = \begin{cases} P^{Bd}_{max,i}, & when \quad SOC_i < SOC_{max,i} \\ 0, & when \quad SOC_i \ge SOC_{max,i} \end{cases},$$

where, $P^{Bc}_{max,i}$, $P^{Bd}_{max,i}$, $SOC_{min,i}$, and $SOC_{max,i}$ refer to the maximum charge power, the maximum discharge power, the minimum SOC and maximum SOC of B_i, respectively. If no battery is deployed along with generators in the i-th subgrid in practice, $P^{Bc}_{max,i}$ and $P^{Bd}_{max,i}$ are set to be zero.

Note that power generation by distributed renewable energy sources, such as photovoltaic panels and wind turbine generators, is assumed to be uncontrollable. These generators have variable power generation capacity, and the total power generation of them at the considered time t is denoted as P^U. Then, the power balance constraint of the entire EI system is expressed as

$$\sum_{i\in\mathcal{V}} (P^G_i + P^B_i) - P^L + P^U = 0, \tag{3}$$

where, P^L is total power demanded by residential loads in the investigated EI system. Based on the components described above, the optimal power dispatching problem is introduced as follows.

In this paper, in order to realize an optimized power dispatch in EI, three factors are under consideration: power generation cost, harmful gas emission, and protection for batteries. In this section, our considered problem is formulated as a convex optimization issue.

Firstly, we formulate the cost function related with power generation cost under the assumption that larger power output would lead to higher consumption of fuels, which means more operational costs. Each generator is designed with a cost function $C_i(\cdot)$ which is

$$C_i(P_i^G) \quad = \quad a_i + b_i P_i^G + c_i {P_i^G}^2, \tag{4}$$

where a_i, b_i and c_i are the coefficients of G_i. From an economic point of view, our objective is to minimize all the cost of generators $\sum_{i \in \mathcal{V}} C_i(P_i^G)$.

Apart from considering the power generation cost, we aim to restrict atmospheric pollutants from generators and reduce the corresponding environmental impact. Such impact is measured by the total amount of atmospheric pollutants, such as sulphur oxides SO_x and nitrogen oxides NO_x produced by controllable generators that rely on fossil fuels. For illustrative purpose, the total *ton/h* emission $E_i(P_i^G)$ of poisonous gas can be expressed as [23]

$$E_i(P_i^G) \quad = \quad \alpha_i + \beta_i P_i^G + \gamma_i {P_i^G}^2 + \omega_i exp(\rho_i P_i^G), \tag{5}$$

where α_i, β_i, γ_i, ω_i and ρ_i are coefficients of G_i emission characteristics.

Next, we consider the rational utilization of batteries. The lifetime of batteries could be significantly influenced when the power throughput of the battery energy storage system keeps at a high level [24]. In this sense, the drastic fluctuations of battery capacity would shorten the battery life. To restrict the charging/discharging power of batteries to a rational level, the loss function is designed as

$$B_i(P_i^B) = {P_i^B}^2. \tag{6}$$

To consider the above three type of optimization issues simultaneously, the overall objective function can be written as

$$\min \quad \lambda_C \sum_{i \in \mathcal{V}} C_i(P_i^G) + \lambda_E \sum_{i \in \mathcal{V}} E_i(P_i^G) + \lambda_B \sum_{i \in \mathcal{V}} B_i(P_i^B), \tag{7}$$

where λ_C, λ_E, and λ_B are weighting coefficients.

The optimization issue can be formulated as

$$\min \quad F(\boldsymbol{P}) = \sum_{i \in \mathcal{V}} \left[f_{G,i}(P_i^G) + f_{B,i}(P_i^B) \right], \tag{8}$$

$$\begin{aligned} s.t. \quad & \textstyle\sum_{i \in \mathcal{V}} P_i^G + P_i^B = D, \\ & \underline{\boldsymbol{P}} \leq \boldsymbol{P} \leq \overline{\boldsymbol{P}}, \end{aligned} \tag{9}$$

where

$$f_{G,i}(P_i^G) = \lambda_C C_i(P_i^G) + \lambda_E E_i(P_i^G),$$

$$f_{B,i}(P_i^B) = \lambda_B B_i(P_i^B),$$

$$\boldsymbol{P} = \left[P_1^G, P_2^G, \ldots, P_N^G, P_1^B, P_2^B, \ldots, P_N^B \right]^\top,$$

$$D = P^L - P^U,$$

$$\underline{\boldsymbol{P}} = \left[P_{min,1}^G, P_{min,1}^G, \ldots, P_{min,N}^G, P_{min,1}^B, P_{min,2}^B, \ldots, P_{min,N}^B \right]^\top,$$

$$\overline{\boldsymbol{P}} = \left[P_{max,1}^G, P_{max,2}^G, \ldots, P_{max,N}^G, P_{max,1}^B, P_{max,2}^B, \ldots, P_{max,N}^B \right]^\top.$$

Here, $f_{G,i}(P_i^G)$ measures the general economic cost and environmental impact of G_i; $f_{B,i}(P_i^B)$ indicates the level of irrational utilization of battery energy storage B_i; P refers to the power input/output of adjustable devices including controllable generators and battery energy storage; The difference between the total power demand of residential loads and the power generation of renewable energy sources is denoted as D for convenience; $\underline{\boldsymbol{P}}$ and $\overline{\boldsymbol{P}}$ are used to describe the lower and upper bounds of the controlled power output/input of generators and battery energy storage devices. In this sense, the considered engineering problem is formulated as a convex optimization problem mathematically.

3 DISTRIBUTED METHOD

In this section, the Lagrangian approach [25] is used to solve the above optimization problem. With the above formulation, a Lagrangian function could be defined as follows

$$\begin{aligned} L(\boldsymbol{P}, \lambda) = & \sum_{i \in \mathcal{V}} \left(f_{G,i}(P_i^G) + f_{B,i}(P_i^B) \right) \\ & -\lambda \left(\sum_{i \in \mathcal{V}} \left(P_i^G + P_i^B \right) - D \right). \end{aligned} \tag{10}$$

The corresponding dual problem of (10) is obtained as

$$\max_{\lambda \in \mathbb{R}^+} \sum_{i \in \mathcal{V}} g_i(\lambda) + \lambda D,$$

where $g_i(\lambda) = \min \left(f_{G,i}(P_i^G) + f_{B,i}(P_i^B) - \lambda(P_i^G + P_i^B) \right)$. For any $\lambda \in \mathbb{R}^+$, $g_i(\lambda)$ has solution given by

$$P_i^G(k+1) = \min \left\{ \max \left\{ \nabla f_{G,i}{}^{-1}, P_{min,i}^G \right\}, P_{max,i}^G \right\},$$

$$P_i^B(k+1) = \min \left\{ \max \left\{ \nabla f_{B,i}{}^{-1}, P_{min,i}^B \right\}, P_{max,i}^B \right\},$$

where $\nabla f_{G,i}{}^{-1}$ and $\nabla f_{B,i}{}^{-1}$ are the inverse function of $\nabla f_{G,i}$ and $\nabla f_{B,i}$. Hence, the gradient method is used to solve the problem as:

$$\lambda(k+1) = \lambda(k) - \gamma(k) \left(\sum_{i \in \mathcal{V}} \left(P_i^G(\lambda) + P_i^B(\lambda) \right) - D \right), \tag{11}$$

where $\gamma(k)$ is the stem size at step k. Motivated by the centralized Lagrangian method, in this paper, a distributed method called subgradient-push method [22] is used to solve the optimization problem. Each agent i maintains scalar variables $w_i(t)$, $y_i(t)$, $\lambda_i(t)$ and $v_i(t)$ for all i. At step k, each agent update its variables as follows:

$$w_i(k+1) = \frac{v_i(k)}{d_i + 1} + \sum_{j \in \mathcal{N}_i} \frac{v_j(k)}{d_i + 1}, \tag{12a}$$

$$y_i(k+1) = \frac{y_i(k)}{d_i + 1} + \sum_{j \in \mathcal{N}_i} \frac{y_j(k)}{d_i + 1}, \tag{12b}$$

$$\lambda_i(k+1) = \frac{w_i(k+1)}{y_i(k+1)}, \tag{12c}$$

$$P_i^G(k+1) = \min \left\{ \max \left\{ \nabla f_{G,i}{}^{-1}, P_{min,i}^G \right\}, P_{max,i}^G \right\}, \tag{12d}$$

$$P_i^B(k+1) = \min \left\{ \max \left\{ \nabla f_{B,i}{}^{-1}, P_{min,i}^B \right\}, P_{max,i}^B \right\}, \tag{12e}$$

$$v_i(k+1) = w_i(k+1) - \gamma(k+1) \left(P_i^G(k+1) + P_i^B(k+1) - D_i \right), \tag{12f}$$

where D_i is a virtual demand connected with agent i, such that $\sum_i^N D_i = D$. The step size $\gamma(k+1)$ satisfies the following decay conditions:

$$\sum_{k=1}^{\infty} \gamma(k) = \infty,$$
$$\sum_{k=1}^{\infty} \gamma^2(k) < \infty,$$
$$\gamma(m) \le \gamma(n), \quad \forall m > n \ge 1.$$

The stop criteria could be expressed as

$$s_1 = \max_i |\lambda_i(k) - \lambda_i(k-1)| < \epsilon_1, \tag{13a}$$
$$s_2 = \max_{i,j} |\lambda_i(k) - \lambda_j(k)| < \epsilon_2. \tag{13b}$$

When s_1 and s_2 satisfy both of these criteria, we consider the solution has been converged. In this sense, our convex optimization problem is solved.

Algorithm 1 Subgradient-Push Method

```
Input: total power demand $P^L$, total power generation of renewable energy sourse $P^U$, the step size $\gamma(k)$
Output: optimal power of each generator and battery $P_i^G$, $P_i^B$
Preparation: $D = P^L - P^U$, $D_i = \frac{D}{N}$
Initialization: $k = 0$, $v_i(0) = 1$, $y_i(0) = 1$
repeat
    for $i \in \mathcal{V}$ do
        compute $w_i(k+1)$, $y_i(k+1)$ with (12a) and (12b)
        compute $\lambda_i(k+1)$ with (12c)
        compute $P_i^G(k+1)$, $P_i^B(k+1)$ with (12d) and (12e)
        update $v_i(k+1)$ with (12f)
    $k = k + 1$
    compute $s_1$, $s_2$
until $s_1 < \epsilon_1$ and $s_2 < \epsilon_2$
```

4 CASE STUDY

In this section, the feasibility and effectiveness of the proposed distributed optimal power dispatching method is evaluated in the EI system depicted in Fig. 1. The overall performance for daily operation of the considered EI system is examined based on the performance indexes in (7).

The constraints for controllable generators and battery energy storage devices as well as the weighting coefficients are listed in Table 1, and the parameters of cost function and emission function can be found in [6]. Two thresholds ϵ_1 and ϵ_2 are set to be 0.001 and 0.45. The optimization problems are solved under the environment of MATLAB 2018a.

Firstly, to evaluate the convergence efficiency of the distributed algorithm, the curve of s_1 and s_2 are shown in Fig. 2, where red lines represent the thresholds of s_1 and s_2, respectively. At a given time, the distributed optimization algorithm 1 will keep searching for the solution for optimal power dispatching problem until both of the stopping criteria for s_1 and s_2 are satisfied. In Fig. 2, the indicators s_1 and s_2 satisfy the stopping criteria after 377 iterations, which suggests that λ of all agents converges to the optimal value.

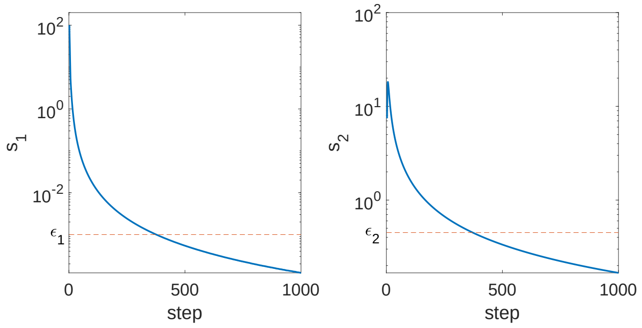

Figure 2: Convergence curve of s_1, s_2

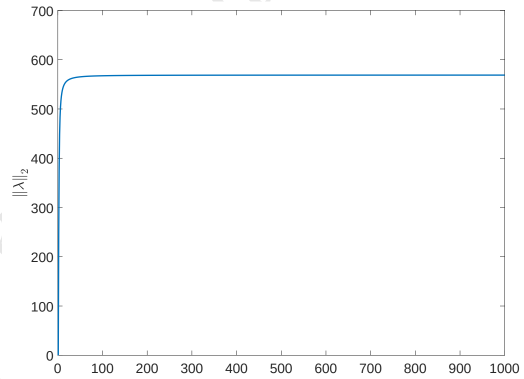

Figure 3: Convergence curve of λ

Table 1: Typical Parameters for Simulation

Parameter	Value	Parameter	Value
$P_{min,1}^G$	0	$P_{max,1}^G$	2MW
$P_{min,2}^G$	0	$P_{max,2}^G$	2MW
$P_{min,3}^G$	0	$P_{max,3}^G$	2MW
$P_{min,4}^G$	0	$P_{max,4}^G$	1.5MW
$P_{min,5}^G$	0	$P_{max,5}^G$	1.5MW
$P_{min,6}^G$	0	$P_{max,6}^G$	1.5MW
$P_{max,1}^{Bd}$	0.12MW	$P_{max,1}^{Bc}$	0.15MW
$P_{max,2}^{Bd}$	0.12MW	$P_{max,2}^{Bc}$	0.15MW
$P_{max,3}^{Bd}$	0.12MW	$P_{max,3}^{Bc}$	0.15MW
$P_{max,4}^{Bd}$	0.08MW	$P_{max,4}^{Bc}$	0.1MW
$P_{max,5}^{Bd}$	0.08MW	$P_{max,5}^{Bc}$	0.1MW
$P_{max,6}^{Bd}$	0.08MW	$P_{max,6}^{Bc}$	0.1MW
λ_C	1	λ_E	500
λ_E	2000		

The power input/output of controllable generators and batteries in the considered time period is shown in Fig. 4 and Fig. 5, respectively. As depicted in Fig. 4, due to the high power generation of renewable energy sources, mostly the photovoltaic panels,

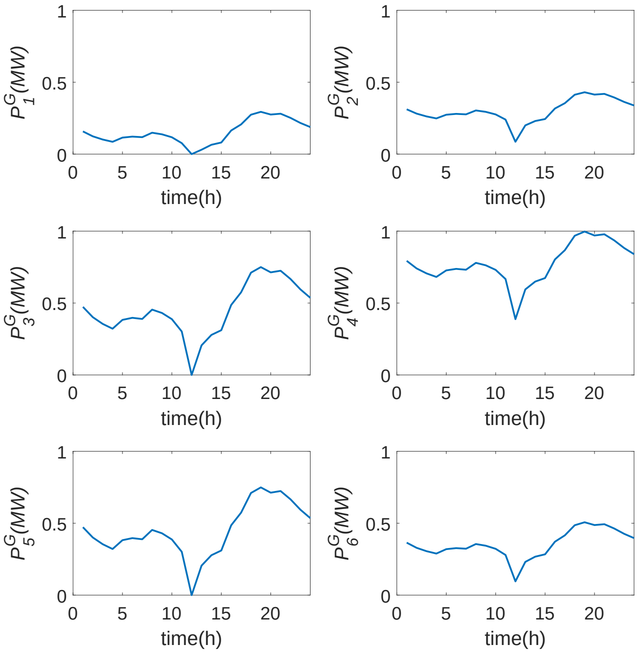

Figure 4: P_G over time with distributed method

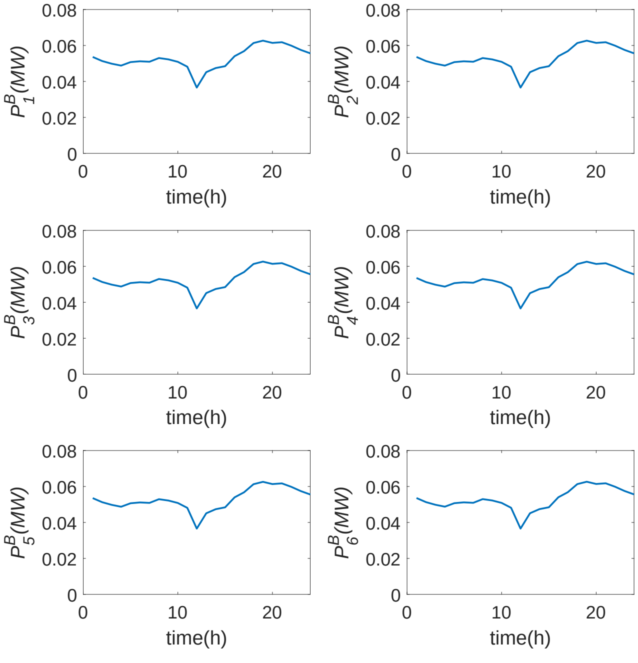

Figure 5: P_B over time with distributed method

the power generation of controllable generators reaches its lowest level around the midday, while more power need to be generated to maintain the balance of demand and supply during the night. The differences of the solution obtained with the adopted distributed optimization method in this paper with with that of the conventional centralized method are shown in Table 2. It is easy to see that the biggest difference among all generators between two results is smaller than 0.012, which fully demonstrates the correctness of our proposed method.

Table 2: Comparison of the Proposed Distributed Power Dispatching Scheme and the Optimal Solution

Generator	Difference(MW)	Battery	Difference(KW)
G_1	0.0004	B_1	0.460
G_2	0.0062	B_2	0.462
G_3	0.0010	B_3	0.469
G_4	0.0117	B_4	0.477
G_5	0.0019	B_5	0.474
G_6	0.0074	B_6	0.462

As one of the main contributions of this paper, the effect of weight coefficients on the proposed power dispatching method is analyzed as follows. Fig. 6 shows how cost varies when λ_E and λ_B are assigned with different values. It's clear that the generation cost increases when either one of λ_E and λ_B increases and another remains unchanged, which means that the weights for the economic operation and environmental impacts should be selected properly based on the practical situations for different application scenarios.

However, the emission curve via λ_E and λ_B is a little complicated. As it is depicted in Fig. 7, there is a small undulation on the surface, which indicates that monotonicity is not always established between the pollutant emission and related weight coefficients. Specifically, the pollutant emission increases when λ_B increases form 0 to 100, while it drops when λ_B continues to increase. Considering the analyses above simultaneously, we can draw the conclusion that cost reduction and emission reduction are not always contradictory. Besides, we can see the emission of pollutant continues to decline along with the increase of λ_E, which behaves as expected.

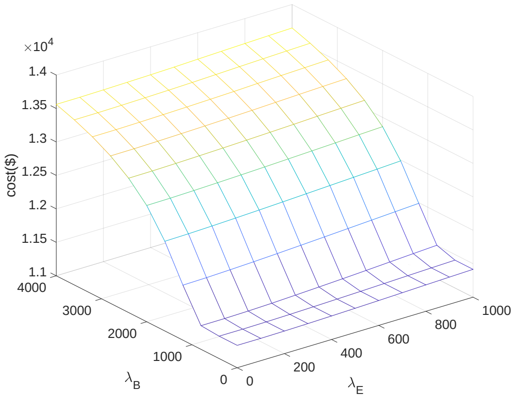

Figure 6: cost curve via λ_E and λ_B.

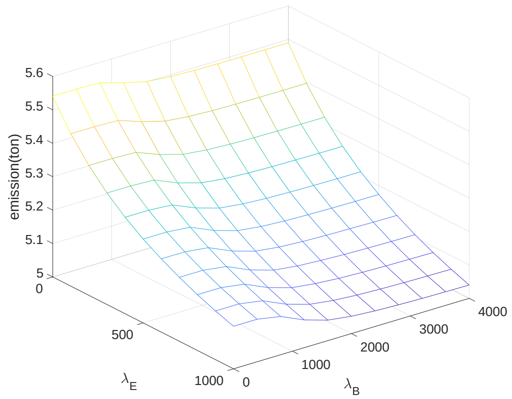

Figure 7: emission curve via λ_E and λ_B.

The numerical examples provided above properly demonstrates the feasibility of the proposed distributed algorithm, and the efficacy of such power dispatching scheme is evaluated undoubtedly.

5 CONCLUSION

In this paper, a distributed scheme considering environmental and economic objective is proposed, such that economic and environmentally friendly power dispatch of a typical EI system could be achieved. It is notable that the economic operation cost of controllable power generators, the environmental impact from pollutant emission of generators and the rational utilization of battery energy storage are taken into account simultaneously. The evaluation results in the case study demonstrate the effectiveness of the proposed decentralized method with the comparison with the solution of typical centralized method.

For the future work, more targets, including system robustness and stability shall be considered in the power dispatching problem. Meanwhile, based on the monitored data, in order to reduce the modelling error, deep reinforcement learning approaches (see, e.g., [28], [29]) might be adopted to solve such problems.

6 ACKNOWLEDGMENTS

This work was funded in part by National Key Research and Development Program of China (Grant No. 2017YFE0132100) and the BNRist Program under (Grant No. BNR2019TD01009).

REFERENCES

[1] J. Rifkin, The third industrial revolution: how lateral power is transforming energy, the economy, and the world, Macmillan, 2011.
[2] J. Cao, H. Hua, and G. Ren, "Energy use and the Internet," The SAGE Encyclopedia of the Internet. Newbury Park, CA, USA: Sage, 2018, pp. 344-350.
[3] X. Han *et al.*, "An open energy routing network for low-voltage distribution power grid," in Proc. 1st IEEE Int. Conf. on Energy Internet, Beijing, China, Apr. 2017, pp. 320-325.
[4] S. Hambridge, A. Q. Huang, and R. Yu, "Solid state transformer (SST) as an energy router: Economic dispatch based energy routing strategy," In Proc. 2015 IEEE Energy Convers. Congress and Exposition, Montreal, QC, Canada, Sept. 2015, pp. 2355-2360.
[5] H. Hua, Y. Qin, C. Hao, and J. Cao, "Stochastic optimal control for energy Internet: A bottom-up energy management approach," IEEE Trans Ind. Inform., vol. 15, no. 3, pp. 1788-1797, Mar. 2019.
[6] M. A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," IEEE Trans. Power Systems, vol. 18, no. 4, pp. 1529-1537, Nov. 2003.
[7] H. Hua, Y. Qin, and J. Cao, "Coordinated frequency control for multiple microgrids in energy Internet: A stochastic H_∞ approach," in Proc. 2018 IEEE PES Innovative Smart Grid Technologies Asia, Singapore, May 2018, pp. 810-815.
[8] H. Hua, C. Hao, Y. Qin, and J. Cao, "Stochastic robust H_∞ control strategy for coordinated frequency regulation in energy Internet considering time delay and uncertainty," in Proc. 13th World Congress on Intelligent Control and Automation, Changsha, China, Jul. 2018, pp. 111-118.
[9] X. Shi, G. Wen, J. Cao and X. Yu, "Model Predictive Power Dispatch and Control With Price-Elastic Load in Energy Internet," IEEE Transactions on Industrial Informatics, vol. 15, no. 3, pp. 1775-1787, March 2019.
[10] H. Hua, Y. Qin, H. Xu, C. Hao, and J. Cao, "Robust control method for DC microgrids and energy routers to improve voltage stability in energy Internet," Energies, vol. 12, Art. no. 1622, 2019.
[11] M. Gao, K. Wang and L. He, "Probabilistic Model Checking and Scheduling Implementation of an Energy Router System in Energy Internet for Green Cities," IEEE Transactions on Industrial Informatics, vol. 14, no. 4, pp. 1501-1510, April 2018.
[12] H. Hua, C. Hao, Y. Qin, J. Cao, and Y. Yang, "Stochastic optimal control scheme for operation cost management in energy Internet," in Proc. 10th IEEE PES Asia-Pacific Power and Energy Engineering Conference, Sabah, Malaysia, Oct. 2018, pp. 445-450.
[13] H. Hua, C. Hao, Y. Qin, and J. Cao, "A class of control strategies for energy Internet considering system robustness and operation cost optimization," Energies, vol. 11, no. 6, Art. no. 1593, 2018.
[14] H. Hua, Y. Qin, J. Geng, C. Hao, and J. Cao, "Robust mixed H_2/H_∞ controller design for energy routers in energy Internet," Energies, vol. 12, no. 3, Art. no. 340, 2019.
[15] H. Pourbabak, J. Luo, T. Chen and W. Su, "A Novel Consensus-Based Distributed Algorithm for Economic Dispatch Based on Local Estimation of Power Mismatch," IEEE Trans. on Smart Grid, vol. 9, no. 6, pp. 5930-5942, Nov. 2018.
[16] F. Guo, C. Wen, J. Mao and Y. Song, "Distributed Economic Dispatch for Smart Grids With Random Wind Power," IEEE Tran. on Smart Grid, vol. 7, no. 3, pp. 1572-1583, May 2016.
[17] Q. Sun, R. Han, H. Zhang, J. Zhou and J. M. Guerrero, "A Multiagent-Based Consensus Algorithm for Distributed Coordinated Control of Distributed Generators in the Energy Internet," IEEE Transactions on Smart Grid, vol. 6, no. 6, pp. 3006-3019, Nov. 2015.
[18] H. Zhang, Y. Li, D. W. Gao and J. Zhou, "Distributed Optimal Energy Management for Energy Internet," IEEE Transactions on Industrial Informatics, vol. 13, no. 6, pp. 3081-3097, Dec. 2017.
[19] H. Xing, Y. Mou, M. Fu and Z. Lin, "Distributed Bisection Method for Economic Power Dispatch in Smart Grid," IEEE Trans. on Power Systems, vol. 30, no. 6, pp. 3024-3035, Nov. 2015.
[20] Y. Wang, L. Wu and S. Wang, "A Fully-Decentralized Consensus-Based ADMM Approach for DC-OPF With Demand Response," IEEE Transactions on Smart Grid, vol. 8, no. 6, pp. 2637-2647, Nov. 2017.
[21] T. Yang et al., "A Distributed Algorithm for Economic Dispatch Over Time-Varying Directed Networks With Delays," in IEEE Trans. on Industrial Electronics, vol. 64, no. 6, pp. 5095-5106, June 2017.
[22] A. Nedić and A. Olshevsky, "Distributed Optimization Over Time-Varying Directed Graphs," in IEEE Trans. on Automatic Control, vol. 60, no. 3, pp. 601-615, March 2015.
[23] R. Yokoyama, S. H. Bae, T. Morita, and H. Sasaki, "Multiobjective generation dispatch based on probability security criteria," IEEE Trans. Power Syst., vol. 3, pp. 317-324, Feb. 1988.
[24] Y. Qin, H. Hua, and J. Cao, "Stochastic optimal control scheme for battery lifetime extension in islanded microgrid," IEEE Trans Smart Grid, vol. 10, no. 4, pp. 4467-4475, Jul. 2019.
[25] D. P. Bertsekas, Nonlinear Programming. Belmont, MA, USA: Athena Scientific, 1999.
[26] S. Kar and G. Hug, "Distributed robust economic dispatch in power systems: A consensus + innovations approach," 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, 2012, pp. 1-8.
[27] F. A. Mohamed and H. N. Koivo, "System Modelling and Online Optimal Management of MicroGrid Using Multiobjective Optimization," 2007 International Conference on Clean Electrical Power, Capri, 2007, pp. 148-153.
[28] H. Hua, Y. Qin, C. Hao, and J. Cao, "Optimal energy management strategies for energy Internet via deep reinforcement learning approach," Applied Energy, vol. 239, pp.598-609, 2019.
[29] J. Cao, W. Zhang, Z. Xiao, and H. Hua, "Reactive power optimization for transient voltage stability in energy Internet via deep reinforcement learning approach," Energies, vol. 12, art. no. 1556, 2019.