A Model Predictive Control Based Distributed Coordination of Multi-microgrids in Energy Internet

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Abstract This paper focuses on the development of optimization-based distributed scheduling strategies for the coordination of an energy internet (EI) with multi-microgrids with consideration of forecast uncertainties. All microgrids have flexible loads, schedulable loads and critical loads; some microgrids have distributed generators, such as micro-turbines, wind turbines, photovoltaic panels; besides, a few microgrids have energy storage devices, such as battery storage. Each microgrid is considered as an individual entity and has its individual objective, these objective functions of microgrids are formulated by mixed integer programming (MIP) models. A game theory based parallel distributed optimization algorithm is proposed to coordinate the competitive objectives of the microgrids with only a little information interaction. A model predictive control (MPC) framework which integrates the distributed optimization algorithm is developed to reduce the negative impacts introduced by the uncertainties of the EI. Simulation results show that our method is flexible and efficient.

Key words Energy internet (EI), game theory, model predictive control (MPC), multi-microgrids, parallel optimization

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Nomenclature

A. Index

t	time index
i	microgrid index
k	iteration step index
a	index of schedulable appliances in microgrid i

B. Constants

M	set of microgrids in the EI system ($i \in M$)
T	number of periods for the control horizon ($t \in T$)
N	a preset iteration coefficient used for accelerating the convergence speed
$A_{i,s}$	set of schedulable appliances in microgrid i ($a \in A$)
Δt	time interval of each period (h)
$P_{i,l}^{\max}, P_{i,O}^{\max}$	the rated power that can be purchased/sold from/to the utility for microgrid i (kW)
$E_{i,E}^{\max}, E_{i,E}^{\min}$	the maximum, minimum available energy level of the ESD unit in microgrid i (kWh)
$E_{i,E}^{\text{init}}$	the initial energy level of ESD unit in microgrid i (kWh)
$P_{i,Ec}^{\max}, P_{i,Ec}^{\min}$	the maximum, minimum charging power of the ESD unit in microgrid i (kW)
$P_{i,Ed}^{\max}, P_{i,Ed}^{\min}$	the maximum, minimum discharging power of the ESD unit in microgrid i (kW)
$\eta_{i,Ed}, \eta_{i,Ec}$	discharging, charging efficiency of the ESD unit in microgrid i (%)
$\varepsilon_{i,E}$	self-discharging rate of the ESD unit in microgrid i (kWh/h)
$c_{i,E}^{\text{O\&M}}$	operation and maintenance cost of the ESD unit in microgrid i ($)
$c_{i,E}^{\text{switch}}$	status switch cost of the ESD unit in microgrid i ($)
$P_{i,\text{DDG}}^{\max}, P_{i,\text{DDG}}^{\min}$	the maximum, minimum allowed power output of the DDG unit in microgrid i (kW)
$T_{i,\text{DDG}}^{\text{down}}, T_{i,\text{DDG}}^{\text{up}}$	the minimum down, operation time of the DDG unit in microgrid i (h)
$c_{i,\text{DDG}}^{\text{down}}, c_{i,\text{DDG}}^{\text{up}}$	shut-down, start-up cost of the DDG unit in microgrid i ($)
$R_{i,\text{DDG}}$	the maximum ramp down/up power rate of the DDG unit in microgrid i (kW)
$c_{i,\text{DDG}}^{1}, c_{i,\text{DDG}}^{2}$	cost coefficients of the DDG unit in microgrid i ($\$/\text{kW}^2, \$/\text{kW}$)
$\alpha 1, \alpha 2$	cost coefficients of the utility generator ($\$/\text{kW}^2, \$/\text{kW}$)
$l_{i,a}^{\min}, l_{i,a}^{\max}$	the minimum, maximum load demand of appliance a for microgrid i (kW)
$l_{i,B}^{\max}$	rated capacity of the critical loads in microgrid i (kW)
$P_{i,PV}^{\max}$	rated power capacity of the PV plant in microgrid i (kW)
$P_{i,\text{wind}}^{\max}$	rated power capacity of the wind farm in microgrid i (kW)
$T_{i,a}^{\text{start}}, T_{i,a}^{\text{end}}$	start time, deadline of appliance a for microgrid i (h)
$E_{i,a}$	total energy demand of the appliance a for microgrid i (kWh)
D_i	spinning reserve ratio for microgrid i (%)
$\xi_1, \xi_2, \xi_3, \xi_4$	preset stopping criteria for the distribution optimization algorithm
$\theta_{i,F}^{\max}$	the maximum curtailment ratio of flexible loads in microgrid i (%)
$c_{i,F}^{\text{curt}}$	penalty cost coefficient for curtailing flexible loads in microgrid i
$P_u^{\max}, P_u^{\min}$	the maximum, minimum power limit of the utility generator (kW)

C. Parameters

$P_{i,\text{wind}}(t)$	power output of the wind turbines in microgrid i at time t (kW)
$P_{i,PV}(t)$	power output of the PV plant in microgrid i at time t (kW)
$l_{i,B}(t)$	demand of the critical loads in microgrid i at time t (kW)
$l_{i,F}(t)$	demand of the flexible loads in microgrid i at time t (kW)
$p_u(t)$	base electricity price for the utility company ($/kWh)
$p_{i,b}(t), p_{i,s}(t)$	buying, selling electricity price for microgrid i at time t ($)

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$p_{i,b}(t), p_{i,s}(t)$	buying, selling price coefficient
D. Variables	
$P_{i,I}(t), P_{i,O}(t)$	power imported/exported from/to the utility for microgrid i at time t (kW)
$\delta_{i,I}(t), \delta_{i,O}(t)$	purchasing, selling power status for microgrid i at time t (0/1)
$P_{i,Ec}(t), P_{i,Ed}(t)$	charging, discharging power rate of the ESD unit for microgrid i at time t (kW)
$\delta_{i,Ec}(t), \delta_{i,Ed}(t)$	charging, discharging status of the ESD unit for microgrid i at time t (0/1)
$E_{i,E}(t)$	energy level of the ESD unit for microgrid i at time t (kWh)
$P_{i,\mathrm{DDG}}(t)$	power output of the DDG unit for microgrid i at time t (kWh)
$\delta_{i,\mathrm{DDG}}(t)$	operation status of the DDG unit for microgrid i at time t (0/1)
$\theta_{i,F}(t)$	curtailment ratio of the flexible loads for microgrid i at time t (%)
$l_{i,a}(t)$	load demand of appliance a for microgrid i at time t (kW)

1 Introduction

The energy internet (EI) is an interesting concept for integrating more distributed energy resources, improving power quality and reliability, and reducing greenhouse gas emissions [1]−[3]. This grid includes advanced digital meters, distribution automation, communication systems and distributed energy resources [4]−[7]. Since more kinds and amounts of devices are integrated and much more data are needed to be collected and analyzed, the optimization and scheduling of the energy Internet (EI) becomes more complex than the traditional power system. To manage and operate such a complex infrastructure efficiently and reliably, a unit of the grid, known as microgrid (or energy local network) [8], [9], has been emerged as a promising platform for the EI to integrate and coordinate a large number of distributed energy resources in a decentralized way [10], [11].

A microgrid or an energy local network is a relatively small-scale localized power system that can distribute generation and load demand in a small geographic area more flexibly and reliably. It typically includes a cluster of dispatchable distributed generators (DDGs) such as microturbines and diesel generators, non-dispatchable renewable energy resources (RERs) such as wind turbines and photovoltaic panels, energy storage devices (ESDs) such as battery storage, various types of smart loads such as heating, ventilating, air conditioning and washing machine, and some other onsite electric components [12]. It can be operated in either grid connected mode or in islanded mode when there are external faults or to gain economic advantages.

As an important element of the EI, many studies have been made in the literature on the energy management of the microgrid. Albadi and Saadany [13] present a summary of demand response in deregulated electricity markets and some utilities' experiences with different demand response programs are discussed. Chia *et al.* [14] discuss the demand response management with multiple utility companies, and a two-level non-cooperative game model is proposed to express the interaction between utility companies and residential users. Su and Wang [15] review the energy management systems (EMSs) in microgrid operation. Chen *et al.* [16] propose an model predictive control (MPC)-based load scheduling approach for a home microgrid which considers electricity price uncertainties. Parisio *et al.* [17] provide a comprehensive model of microgrid and an MPC-based approach to efficiently optimize microgrid operation with considering time-varying requests and operation constraints. Zhu and Hug [18] present a stochastic approach to optimally dispatch the power of a microgrid. Su *et al.* [19] propose an MPC-based power dispatch approach with considering plug-in electric vehicles.

Due to the EI can be considered as the Smart Grid 2.0 [20], the advanced technologies can be utilized for the future EI system. Tang *et al.* [21]−[23] propose a goal representation adaptive dynamic programming (GRADP) method to control and operate a smart grid. Amini *et al* [24] investigate two decomposition methods for solving the optimization problem in security constrained economic dispatch (SCED) of the power system. The advantages and drawbacks of each method are discussed in terms of accuracy and information privacy. Deng *et al.* [25] discuss a MPC based bilinear model to obtain optimal set-points to satisfy the campus cooling demands and minimize the daily electricity cost for a campus central plant which is equipped with a bank of multiple electrical chillers and a thermal energy storage.

Furthermore, the coordinated control of the microgrids, independent consumers and utility companies in an EI system can be considered as one of the most key problem of developing EI technology and it is the main topic of this paper. Huber *et al.* [26] investigate the benefits of a community home microgrids and the coordination of smart homes. Olivares *et al.* [27] propose an MPC based approach to optimally dispatch the energy storage units, controllable generators and smart loads in medium-voltage isolated microgrids. Zhou *et al.* [28] describe the operation of a central controller for microgrids on neighboring islands to dynamically dispatch the production of local distributed energy resources. Ai and Xu [29] propose a centralized co-operation model for a smart distribution system which includes multi-microgrids. However, the above studies all are centralized approaches, heavy communication and computation burden will be yielded with the expanding of the system structure. In addition, these approaches cannot deal with the case that the microgrids have competitive objectives, they only aim to minimize the total operation cost of the whole EI system, but do not consider the distinct objectives of the individual microgrid.

Distributed control strategies could reduce the requirements to manipulate large quantities of information exchanges related to the complex network of microgrids. Fathi and Bevrani [30] study the energy consumption scheduling of connected microgrids with considering uncertainties in a semi-distributed approach. Wang *et al.* [31] present a stochastic bi-level based decentralized power dispatch model for the coordinated operation of multiple microgrids where uncertainties of RERs outputs are considered. Kamyab *et al.* [32] analyze the demand response problem in a smart grid with multiple utility companies and multiple customers. Two non-cooperative games: the supplier and customer side games developed, the existence and uniqueness of the Nash equilibrium in the mentioned games are studied. Asimakopoulou *et al.* [33] present a leader-follower strategy for analyzing competitive situations of hierarchical decision making between microgrids and large central production unit. A stackel-berg game is implemented to decide the real-time power exchange. Yang *et al.* [34] study a parallel distributed framework for demand response in smart grids which includes users with

RERs. The goal is to optimize the load schedule of users to minimize the utility company's cost and user payments.

Several factors, such as the power production of the RERs and load demand varying over the time, and the different microgrids having distinct objectives, make the traditional scheduling strategies unable to deal with the scheduling problems of EI efficiently. MPC is an advanced method for process control, which has been widely used in a variety of complex dynamic systems [35]. In recent years, MPC has drawn much attention of the energy management community due to its ability to incorporate both forecasts and newly updated information to decide the future behaviors of the system and handle constraints efficiently. As the emerging of smart grid and EI technologies, the MPC-based distributed algorithms are also considered as a promising way to efficiently handle the cooperation problems of the large power system which consisted with multiple subsystems, due to it can not only keep the advantage of MPC technology but also can decompose the complexity of the optimization problem with a distributed way [36].

In this paper, we propose a MPC-based distributed optimal scheduling strategy for an EI which includes a utility company, multiple microgrids and a few independent consumers. This strategy is used for the coordinated operation of entities such as microgrids, utility and consumers, which have distinct objectives. All the microgrids and independent consumers are autonomously scheduled by their own EMSs. The EMSs send their total purchasing/selling plans to the EI operator and receive the real-time retail electricity price from the EI operator in each optimization iteration, which can effectively reduce the computation burden comparing to the centralized optimization approaches, as well as avoid infringing the privacies due to each EMS does not need to disclose the operation plan of the dispatchable units to other EMSs. In addition, this strategy can save much communication costs and time comparing to the sequential distributed approaches used in [37].

More specially, the contribution of the present paper is summarized in the following:

1) A MIP-based optimization model of the microgrid which considers many key features, such as minimum running/stopping time of the DDGs, charging/discharging switch of the ESDs, and various kinds of smart loads is proposed.

2) MPC-based distributed optimization strategy which not only can coordinate the operation of entities in the EI system with competitive objectives but also can effectively handle the uncertainties introduced by loads and RERs.

3) The proposed method is verified by simulation-based case studies.

The rest of this paper is organized as follows. Section 2 presents the model of the entities in the EI and the retail electricity price mechanism. Section 3 introduces the MPC based distributed control scheme for coordinating the operation of the entities in the EI. Case studies and simulations are implemented in Section 4. Finally, conclusions are drawn in Section 5.

2 System Model and Problem Formulation

Consider an EI consists of a set of microgrids, several independent consumers and a utility company, interconnected through a power transmission infrastructure and a communication network, as shown in Fig. 1. For saving space and better understanding, we also consider the independent consumers as microgrids which have neither generators nor ESDs. The demand of each microgrid can be supplied from the internal sources (such as its own RERs, DDG, and ESD) or/and from the other sources (such as other microgrids and the utility company) throughout the EI system. The EI operator controls the generation output of the utility company, decides the retail selling/purchasing electricity price and sends this price information to all the microgrids, and receives information from the microgrids. The microgrid EMS controls the load schedule of the smart loads, the output of its own DDGs, the charging/discharging plan of its own ESDs, and the purchasing or selling power plan of the microgrid. The determination of the EI operator is influenced by the actions of the EMSs, and vice versa. The objective of the EMS in each entity is to optimize its individual objective and to increase its own benefit, and the variables of each entity are distinct. Therefore, the coordination of the EI system can be formulated as competitive games model.

2.1 System Modeling

1) Loads Model

The loads in microgrid i consist of the critical loads, schedulable loads, and flexible loads [34], as shown in (1).

$$l_i(t) = l_{i,B}(t) + l_{i,F}(t)(1 - \theta_{i,F}(t)) + \sum_{a=1}^{A_{i,S}} l_{i,a}(t). \tag{1}$$

For the schedulable appliance α, there are start time and deadline constraints for completing its task, and the lower and upper power bounds should be satisfied during its operation time, as shown in (2). In addition, a certain energy must be consumed for this task, as shown in (3).

$$\begin{cases} l_{i,a}^{\min} \le l_{i,a}(t) \le l_{i,a}^{\max}, & \text{if} \quad T_{i,a}^{\text{start}} \le t \le T_{i,a}^{\text{end}} \\ l_{i,a}(t) = 0, & \text{otherwise} \end{cases} \tag{2}$$

$$\sum_{t=T_{i,a}^{\text{start}}}^{T_{i,a}^{\text{end}}} l_{i,a}(t)\Delta t = E_{i,a}. \tag{3}$$

For the flexible loads, the power adjustment ratio must be bounded in a certain range to keep the user's comfort, as expressed in (4).

$$0 \le \theta_{i,F}(t) \le \theta_{i,F}^{\max}. \tag{4}$$

As we all know, the critical loads cannot be adjusted or scheduled, their power demand should be satisfied all the time. However, their actual and forecasted power demand both cannot excess the corresponding capacity limit, as denoted in (5).

$$0 \le l_{i,B}(t) \le l_{i,B}^{\max}. \tag{5}$$

2) Generators Model

In this EI, the microgrids may have DDGs and RERs. The DDG model used in this paper is based on a microturbine [17]. Its power output, minimum up time, minimum down time, and ramp up/down power constraints are illustrated in (6)−(9), respectively.

$$P_{i,\text{DDG}}^{\min}\delta_{i,\text{DDG}}(t) \le P_{i,\text{DDG}}(t) \le \delta_{i,\text{DDG}}(t)P_{i,\text{DDG}}^{\max} \tag{6}$$

$$\delta_{i,\text{DDG}}(t) - \delta_{i,\text{DDG}}(t-1) \le \delta_{i,\text{DDG}}(\tau_1) \tag{7}$$

$$\delta_{i,\text{DDG}}(t-1) - \delta_{i,\text{DDG}}(t) \le \delta_{i,\text{DDG}}(\tau_2) \tag{8}$$

$$-R_{i,\text{DDG}}(t-1) \le P_{i,\text{DDG}}(t) - P_{i,\text{DDG}}(t-1) \le R_{i,\text{DDG}}(t) \tag{9}$$

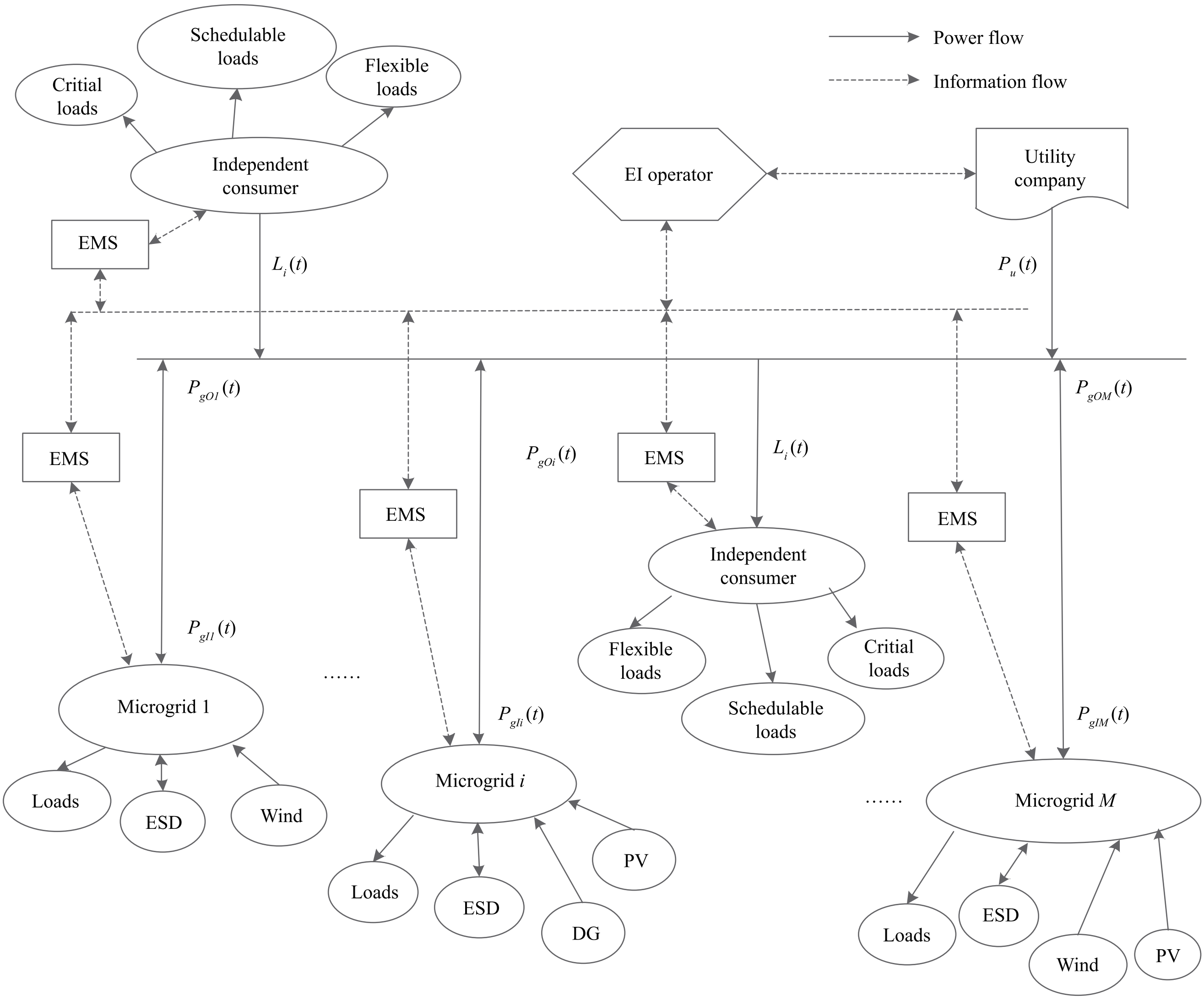

Fig. 1. Schematic of an EI.

where τ_1, τ_2 are introduced auxiliary parameters, and $\tau_1 = t+1, \dots, \min(t+T_{i,\mathrm{DDG}}^{\mathrm{up}}-1, T)$, $\tau_2 = t+1, \dots, \min(t+T_{i,\mathrm{DDG}}^{\mathrm{down}}-1, T)$, and they are used for expressing the minimum up and down time constraints, respectively.

Though the output of the RERs is considered as non-dispatchable, for preventing large errors introduced by forecast models, the forecasted outputs of PV and wind generators must be in certain bounds in each period, as shown in (10) and (11).

$$0 \le P_{i,PV}(t) \le P_{i,PV}^{\max} \tag{10}$$

$$0 \le P_{i,\mathrm{wind}}(t) \le P_{i,\mathrm{wind}}^{\max} \tag{11}$$

3) ESD Unit Model

ESD units play an important role in the power system operation, control and management [38]. ESD unit model in this paper is based on battery storage technology. It is modeled by the maximum and minimum state of charge (SOC) level, charging power limit, discharging power limit, and operation status, as shown in (12)−(15), respectively. In addition, the dynamic model of the ESD unit is very important, the SOC level at the beginning of the next period is determined by the current period SOC level and the charging or discharging operation during this period, as expressed in (16).

$$E_{i,E}^{\min} \le E_{i,E}(t+1) \le E_{i,E}^{\max} \tag{12}$$

$$\delta_{i,Ec}(t)P_{i,Ec}^{\min} \le P_{i,Ec}(t) \le \delta_{i,Ec}(t)P_{i,Ec}^{\max} \tag{13}$$

$$\delta_{i,Ed}(t)P_{i,Ed}^{\min} \le P_{i,Ed}(t) \le \delta_{i,Ed}(t)P_{i,Ed}^{\max} \tag{14}$$

$$\delta_{i,Ec}(t) + \delta_{i,Ed}(t) \le 1 \tag{15}$$

$$E_{i,E}(t+1) = +E_{i,E}(t) + (\eta_{i,Ec}P_{i,Ec}(t) - 1/\eta_{i,Ed}(t) - \varepsilon_{i,E})\Delta t \tag{16}$$

where $E_{i,E}(1) = E_{i,E}^{\mathrm{init}}$ indicates the initial SOC level at the beginning of the optimization process, $t \in [1, T]$. For effectively responding to the emergency conditions, the energy level of the ESD at the beginning of each day must be kept near its initial level.

4) Interaction With Other Microgrids

When a microgrid operates in grid-connected mode, it can purchase/sell electricity from/to the utility company. For encouraging the local use of RERs power output, guaranteeing the benefits of microgrid owners, and inciting the utility company to buy electricity from the microgrid, we set the electricity purchasing price and selling price different at the same time. The detailed price mechanism will be introduced in the following. Therefore, for more effectively operating the microgrids, we introduce auxiliary variables $\delta_{i,l}(t)$ and $\delta_{i,O}(t)$ to model the possibility either to purchase from or to sell energy to the utility grid. The constraints of the purchasing power, selling power and operation status at the point of common coupling (PCC) for microgrid i can be illustrated as (17)−(19), respectively.

$$0 \le P_{i,l}(t) \le P_{i,l}^{\max}\delta_{i,l}(t) \tag{17}$$

$$0 \le P_{i,O}(t) \le P_{i,O}^{\max}\delta_{i,O}(t) \tag{18}$$

$$\delta_{i,l}(t) + \delta_{i,O}(t) \le 1. \tag{19}$$

5) Power Balance Constraint

For each microgrid, power balance constraint must be satisfied in every period, as shown in (20).

$$\begin{aligned} &l_i(t) + P_{i,Ec}(t) + P_{i,O}(t) \\ &= P_{i,Ed}(t) + P_{i,l}(t) + P_{i,\mathrm{DDG}}(t) + P_{i,PV}(t) + P_{i,\mathrm{wind}}(t). \end{aligned} \tag{20}$$

Meanwhile, for the whole EI, the total generated power of the utility company plus the buyback power from all the microgrids must equal to the total power purchased by the microgrids.

$$P_u(t) + \sum_{i=1}^{M} P_{i,O}(t) = \sum_{i=1}^{M} P_{i,I}(t). \tag{21}$$

Besides, the generators of utility should be operated in their power limit.

$$P_u^{\min} \le P_u(t) \le P_u^{\max}. \tag{22}$$

For reducing the negative impacts introduced by randomness of the RERs outputs and the loads demands, extra spinning reserve constraints must be considered for the EI system.

$$\begin{aligned} &(1 + D\_i) \sum_{i=1}^{M} l_i(t) \le \sum_{i=1}^{M} \delta_{i,Ed}(t) P_{i,Ed}^{\max} + \sum_{i=1}^{M} P_{i,I}^{\max}\delta_{i,I}(t) \\ &+ \sum_{i=1}^{M} \delta_{i,\mathrm{DDG}}(t) P_{i,\mathrm{DDG}}^{\max} + \sum_{i=1}^{M} P_{i,PV}(t) \\ &+ \sum_{i=1}^{M} P_{i,\mathrm{wind}}(t) P_u^{\max}. \end{aligned} \tag{23}$$

6) Retail Electricity Price Mechanism

The fuel cost of the utility generators and the DDGs are all non-decreasing convex function of their own generation. In most conditions, this convex function can be expressed as a quadratic function in (24).

$$\begin{aligned} &C_u(t) = a1 \cdot (P_u(t))^2 + a2 \cdot P_u(t) \\ &C_{i,\mathrm{DDG}}(t) = c_{i,\mathrm{DDG}}^1 \cdot (P_{i,\mathrm{DDG}}(t))^2 + c_{i,\mathrm{DDG}}^2 \cdot P_{i,\mathrm{DDG}}(t). \end{aligned} \tag{24}$$

Therefore, the basic electricity price of the utility can be denoted as follows:

$$p_u(t) = a1 \cdot P_u(t) + a2. \tag{25}$$

Based on the overall consideration of increasing onsite RERs use, inciting the utility to buy electricity from the microgrids and the rate-of-return regulations [39], we set the retail buying and selling electricity price for the microgrids as (26) and (27), respectively.

$$p_{i,b}(t) = p_{i,b}(t)p_u(t) \tag{26}$$

$$p_{i,s}(t) = p_{i,s}(t)p_u(t) \tag{27}$$

where $p_{i,b}(t) > 1$ to guarantee the rate-of-return of the utility company, and $\varsigma < \rho_{i,s}(t) \le 1$ to incite the EI operator to buy the surplus energy of the microgrids and guarantee the user's benefits. ς is a preset coefficient.

2.2 Cost Modeling

For microgrid i, the objective is to minimize the total operation cost in the future hours, which includes: the operation cost of the DDG units and ESD units, the purchasing electricity cost by importing power from the utility company, the revenue from electricity sold back to the utility company. Due to the capital costs of the power devices are independent of the schedule, we do not consider them. Therefore, the total operation cost of microgrid i in the future hours based on the forecasts can be generated as follows (denoted as Ψ_i).

$$\begin{aligned} \Psi_i = &\sum_{t=1}^{T} \{-P_{i,O}(t)p_{i,s}(t)\Delta t + P_{i,I}(t)\Delta t \\ &+ [C_{i,\mathrm{DDG}}(t) \\ &+ C_{i,\mathrm{DDG}}^{\mathrm{up}} \max(\delta_{i,\mathrm{DDG}}(t) - \delta_{i,\mathrm{DDG}}(t-1), 0) \\ &+ C_{i,\mathrm{DDG}}^{\mathrm{down}} \max(\delta_{i,\mathrm{DDG}}(t-1) - \delta_{i,\mathrm{DDG}}(t), 0)\Big] \\ &+ \Big[c_{i,E}^{\mathrm{O\&M}}(P_{i,Ec}(t) + P_{i,Ed}(t))\Delta t \\ &+ c_{i,E}^{\mathrm{switch}} \max(\delta_{i,I}(t) - \delta_{i,I}(t-1), 0) \\ &+ c_{i,E}^{\mathrm{switch}} \max(\delta_{i,O}(t) - \delta_{i,O}(t-1), 0)\Big] \\ &+ c_{i,F}^{\mathrm{curt}}\theta_{i,F}(t) l_{i,F}(t)\Delta t\big\} \quad \text{s. t. } (1)-(23). \end{aligned} \tag{28}$$

In (28), the first term is the revenue of selling power back to the utility; the second term is the cost of purchasing energy from the utility; the third term denotes the operation costs of the DDG units, which include fuel consuming cost, startup cost, and shut down cost; the fourth term is the operation cost of ESDs, which comprises operation and maintenance cost, charge-to-discharge switch cost, and discharge-to-charge switch cost; the last term is the flexible power curtailment penalty cost.

The total cost of the utility includes fuel consuming cost and purchasing cost from all microgrids (denoted as Ψ_u).

$$\Psi_u = \sum_{t=1}^{T} C_u(t) + \sum_{t=1}^{T} P_{i,O}(t)p_{i,s}(t)\Delta t \qquad \text{s. t. } (1)-(23). \tag{29}$$

In (29), the first term is the fuel cost of the utility and the second term is the purchasing electricity cost from all microgrids.

The objective of the ith microgrid is to minimize its total operation cost Ψ_i in the future hours by optimizing the dispatchable units in it. The goal of the utility would be to minimize its total cost Ψ_u. In practice, the schedules of each microgrid are calculated by trade-off between the retail purchasing/selling electricity and its total cost, furthermore, the decisions of each microgrid are affected by the other microgrids. Therefore, it is intractable to minimize the total cost of the whole EI system with respect to the objective of each individual microgrid and the utility company in a centralized way. The reasonable way is to allow each microgrid to optimize its own operation schedules based on its EMS in a competitive way.

3 MPC Based Distributed Optimization

During the recent years, MPC framework has attracted many considerations in power system energy management due to the following reasons [25], [39], [40]: 1) the control action is based on the forecasts of the future time and the newly updated information; 2) a feedback and rolling horizon mechanism is implemented to make the system can adjust the control actions according to the varying information, this mechanism can handle stochastic factor effectively; and 3) it can efficiently handle different kinds of constraints, linear or nonlinear. Since the scheduling of the EI system is mainly completed by coordinating the operation of microgrids which has competitive objectives, a MPC-based distributed optimization strategy should be proposed.

The coordination procedures for MPC-based distributed optimization for an EI are as follows:

1) At the end of time step $t-1$, the EMS of microgrid i obtains the updated system state of all the components in this microgrid, including: SOC level of the ESD unit $E_{i,E}(t)$, power output $P_{i,\mathrm{DDG}}(t)$ and operation status $\delta_{i,\mathrm{DDG}}(t)$ of the DDG unit, the curtailed flexible load $l_{i,F}(t)\theta_{i,F}(t)$, and the control action of the schedulable load $l_{i,a}(t)$. Then the EMS calculates the forecasted data of the load demand, PV generation and wind production from t to $t+T$.

2) The microgrids obtain their optimal control sequence by solving (30) independently and parallel with Algorithm 2 shown in Table I in iteration $k(k>0)$ and receive the newly updated retail electricity price $p_{i,s}^{k+1}(\tau)$, $p_{i,b}^{k+1}(\tau)$ in iteration $k+1$ until the equilibrium among the microgrids have reached.

3) At time step t, only the first element of the optimal control sequences of the dispatchable units in each microgrid obtained in step 2) can be implemented, the insufficient power due to the forecast errors will be compensated by the fast responsive generators of the utility company, in the opposite case, the surplus power will be abandoned, and then the EI operator corrects and updates the parameters of the RERs output and load demand forecast model with the new data.

4) Implement from step 1) again.

For ensuring the parallel distributed optimization algorithm in Table I can achieve convergence, a penalty function (denoted as Φ_i^k) in [41] is introduced to limit the power changes of all the dispatchable units between two steps. It aims to prevent the big changes of one dispatchable unit in two successive iterations by penalizing the distance between two iteration steps, as shown in (30).

$$\Phi_i^k=\lambda_i^k(||(P_{i,Ed}^k(\tau)-P_{i,Ec}^k(\tau)))-(P_{i,Ed}^{k-1}(\tau)-P_{i,Ec}^{k-1}(\tau))||_2^2 + ||l_i^k(\tau)-l_i^{k-1}(\tau)||_2^2+||P_{i,\mathrm{DDG}}^k(\tau)-P_{i,\mathrm{DDG}}^{k-1}(\tau)||_2^2 \tag{30}$$

where λ_i^k is a coefficient to indicate the importance of the ith microgrid in the EI system, which determines the iteration steps needed to achieve convergence. $P_{i,Ed}^k(\tau)$, $P_{i,Ec}^k(\tau)$, $l_i^k(\tau)$, $P_{i,\mathrm{DDG}}^k(\tau)$ denote the determined ESD discharging power, ESD charging power, total load demand and DDG power output for the future hours, respectively in the kth iteration. Since not all the microgrids have all kinds of dispatchable units, thus the expression of (30) maybe different, for example, the expression for the independent users is $\Phi_i^k=\lambda_i^k||\lambda_i^k(\tau)-\lambda_i^{k-1}(\tau)||_2^2$.

According to (30), large λ_i^k value can strictly restrict the changes between two iteration steps, but the convergence needs more number of iterations to achieve. Meanwhile, too small λ_i^k value may cause violent fluctuations between two iteration steps, and cannot guarantee the convergence.

$$\min(\Psi_i^k+\Phi_i^k)\quad \text{s. t. } (1)-(23). \tag{31}$$

In (31), the only information that the ith microgrid needs to determine is its optimal operation schedule is the retail electricity prices. It can protect the user's privacy due to that the EMS does not need to report its detailed operation scheme to other microgrids. Moreover, the distributed optimization algorithm in Table I will stop when the changes of utility cost and power schedules of the microgrids are within the preset thresholds in consecutive two iterations.

Due to the performance of the distributed algorithm presented in Table I is heavily dependent on the value of λ_i^k, thus the choice of λ_i^k should reflect the impacts of the ith microgrid in the EI scheduling, and effectively prevent large changes between two successive iteration steps. Based on this consideration, an adaptive penalty coefficient λ_i^k is proposed which is the trade-off between the step-size and the iteration number.

TABLE I
ALGORITHM FOR PARALLEL DISTRIBUTED OPTIMIZATION METHOD FOR EI SYSTEM

Algorithm 1: for utility at time t
begin
  $k=0$; % iteration counter
  Obtain the initial $P_{i,I}^k(\tau)$, $P_{i,O}^k(\tau)$ of each microgrid according to the random generation technique; $\tau\in[t,t+1,\dots,t+T-1]$
  Calculate utility cost Ψ_u^k according to (29), the retail buying electricity price $p_{i,b}^k(\tau)$ and selling price $p_{i,s}^k(\tau)$ according to (26) and (27), respectively;
  do
   Broadcast updated retail prices to all microgrids;
   Receive the newly updated $P_{i,I}^{k+1}(\tau)$, $P_{i,O}^{k+1}(\tau)$ simultaneously from all the microgrids according to Algorithm 2 shown in the following; $i\in[1,M]$
   Calculate utility cost Ψ_u^{k+1}, retail electricity price $p_{i,s}^{k+1}(\tau)$, $p_{i,b}^{k+1}(\tau)$
   $k:=k+1$;
  until $||\Psi_u^k-\Psi_u^{k-1}||\le\xi_1, ||l^k(\tau)-l^{k-1}(\tau)||\le\xi_2,$
   $|||P_{Ed}^k(\tau)-P_{Ec}^k(\tau)||-||P_{Ed}^{k-1}(\tau)-P_{Ec}^{k-1}(\tau)|||\le\xi_3,$
   $||P_{\mathrm{DDG}}^k(\tau)-P_{\mathrm{DDG}}^{k-1}(\tau)||\le\xi_4$
end

Algorithm 2: for microgrid i at time t
begin
  $k=0$; % iteration counter
  Initialize $P_{i,I}^k(\tau), P_{i,O}^k(\tau)$ according to the random generation technique;
  Report $P_{i,I}^k(\tau)$, $P_{i,O}^k(\tau)$ to the EI operator; $\tau\in[t,t+1,\dots,t+T-1]$
  While
   Update the received retail electricity price $p_{i,s}^k(\tau)$, $p_{i,b}^k(\tau)$ from the EI operator
   Solve the optimization problem (31) and obtain the newly updated $P_{i,I}^{k+1}(\tau)$, $P_{i,O}^{k+1}(\tau)$;
   Report $P_{i,I}^{k+1}(\tau)$, $P_{i,O}^{k+1}(\tau)$ to the EI operator;
   $k:=k+1$;
  end
end

$$\lambda_i^k=\max\{\gamma_i^k,\frac{k}{N}\gamma_i^k\}. \tag{32}$$

Equation (32) indicates that a relatively little coefficient

γ_i^k can make the distributed optimization algorithm converge to a certain range in a few iterations steps, and as the iteration number becomes large enough ($k \geq N$) a larger and larger coefficient $k\gamma_i^k/N$ is generated to constrict the step-size of two iterations steps to ensure convergence of the algorithm.

The coefficient γ_i^k is obtained as following:

$$\gamma_i^k = \pi \cdot \left(\left\| \frac{\sum\limits_{t=1}^{T} P_u^k(t)}{\sum\limits_{t=1}^{T} (P_{i,I}^k(t) + P_{i,O}^k(t))} \right\|_2^2 \right)^{\alpha} \tag{33}$$

where $\alpha > 0$ is a preset constant, $||\cdot||_2^2$ is used to prevent emerging negative value because the microgrid may sell energy back to the utility company, and π is a step-size coefficient which is used to adjust the operation impacts of the microgrids in the EI system. As the amount of the penalty coefficient γ_i^k reflects the importance of the ith microgrid in the EI system, the exchanged power $P_{i,I}^k(t)$, $P_{i,O}^k(t)$ between the microgrid and the utility is chosen.

In (33), a small coefficient γ_i^k is selected for the microgrids whose total power interactions between the microgrid and the utility are large (called large microgrids), otherwise, a large coefficient γ_i^k is selected for the microgrids whose total power interactions between the microgrid and the utility are small (called small microgrids). The small microgrids tend to schedule their dispatchable units without considering the aggregate impacts on the retail price, a large coefficient γ_i^k can effectively constrain the power vary in consecutive iteration steps. However, the retail electricity price has a more significant impact on the large microgrids.

4 Simulation and Results

4.1 General Setup

We consider an EI system with three microgrids, an independent consumer and a utility, as shown in Fig. 1. Each microgrid includes a PV plant and kinds of smart loads, meanwhile, microgrid 2 has a DDG unit instead of the wind farm.

The rated power capacity of the PV plants and wind farms, the rated power can be exchanged between the microgrids and the utility, and the rated power capacity of the critical loads are all listed in Table II, as shown in Fig. 2. The prediction error probabilistic distributions of the load, wind and PV can be estimated with the method described in [42]−[45]. However, as the focus of this paper is on the scheduling and operation strategies, simplified normal distribution models are used for representing the real-time forecast errors of them. Flexible load demand of EI system is assumed as 30 % of the critical load demand at the same time, the maximum allowable curtailment ratio of it is 0.5, and we assume 2.5 times of the base electricity price as a penalty cost coefficient for penalizing the power curtailment of the flexible loads. Since the schedulable loads are consisted of a number of tasks, as shown in Table III, we do not consider the penalty cost. Parameters of the ESD units are denoted in Table IV, the depth of discharge (DoD) for all the ESD units are assumed 80 %, and the initial SOC of each ESD unit is 50 %. Parameters of the DDG unit in microgrid 2 and the generator of the utility company are shown in Table V.

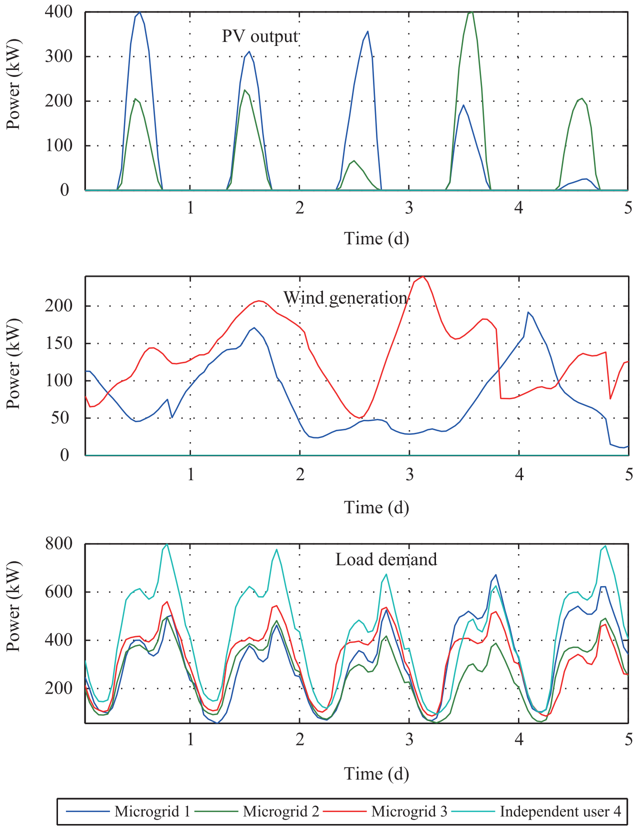

Fig. 2. Data of the EI system needed in this paper.

TABLE II
Power Limits of Microgrids and Independent User

	PV plant	Wind farm	PCC node	Critical load
Microgrid 1	400	192	1200	672
Microgrid 2	400	0	800	496
Microgrid 3	0	240	800	560
Independent user	0	0	1500	800

TABLE III
Parameter of Schedulable Loads

	Power demand (kW)	Operation interval (h)	Time window (h)	Duration (h)
Task 1	22	15−21	6	2
Task 2	28	14−23	9	4
Task 3	45	8−18	10	6
Task 4	37.5	6−24	18	8
Task 5	12	2−22	20	12
Task 6	60	8−22	14	7
Task 7	75	6−24	18	9

The duration of one period is set as an hour, the prediction and control horizon equal to T time intervals, and the total simulation horizon is 5 days. Due to the rate-of-return regulations, we set the real-time retail purchasing electricity price for the microgrid as 1.2 times of the base price, and the real-time retail selling price for the microgrid

TABLE IV
Parameter of ESDs

	Max charge/ discharge power	Min charge/ discharge power	O&M cost	Switch cost	Max energy level	Charge / discharge efficiency
Microgrid 1	160	5	0.05	0.06	320	0.95
Microgrid 2	140	8	0.05	0.05	300	0.95
Microgrid 3	120	6	0.05	0.07	260	0.95

TABLE V
Parameter of Controllable Generators

	Max power	Min power	Ramp rate	Min up/down time	Startup/shut down cost	Cost coefficients
Microgrid 2	150	5	100	2/2	1.2/1.2	0.0042/0.32
Utility	4500	50	-	-	-	0.00048/0.28

is 0.8 times of the base price. Due to the cost of the responsible generators which are operated in the real-time power compensation stage to guarantee the power balance of the EI system are higher than that of the common generators, for saving space and better understanding, we assume that cost coefficients of the responsible generators and the common generators are the same, but the electricity price for the responsible generators is 3 times of the base price.

The parameters of the stopping criteria for the distributed optimization algorithm in Table I is set to be

$$\xi_1 = 0.2, \quad \xi_2 = 0.1, \quad \xi_3 = 0.05, \quad \xi_4 = 0.05.$$

These above parameters are used for determining whether the algorithm has reached its equilibrium. Other parameters used in this paper are set to be

$$N = 16, \quad \rho = 10, \quad \alpha = 1/2.$$

4.2 Simulation Results

In this section we will first verify the superiority of the MPC-based distributed (DMPC) strategy proposed in this paper by comparing its performance with the traditional day-ahead-based distributed (DDA) strategy with considering forecast errors, then we will discuss the impacts of the dispatchable elements such as the ESD units and DDG units in the microgrids' operation optimization, the impacts of the step-size coefficient π will be discussed at last.

All simulations were run on a PC with Intel (R) Core (TM) i5-3470 CPU @3.2 GHz and 8.00 GB memory. The ILOG's CPLEX v.12 optimization solver is utilized for solving the MIP models, MATLAB 2013a and YALMIP toolbox [46] are used for linking the CPLEX solver and computing the optimization model.

4.2.1 Results of the DMPC Strategy and DDA Strategy

Firstly, we will introduce the DDA strategy briefly. It is an open-loop based algorithm [17], whose detailed process is shown as the follows.

1) In the scheduling stage, the EMSs implement the distributed optimization algorithm of Table I at the beginning of the day with the forecasted RERs production and load demand data and obtain the control sequence of the dispatchable units of all microgrids and the generation plan of the utility within this day.

2) In the real-time power compensation stage, all the microgrids will be operated as the control sequence determined in the scheduling stage strictly. The insufficient power will be compensated by the fast responsive generators of the utility, otherwise, the surplus power will be abandoned.

Figs. 3 and 4 denote the operation schedules of the four microgrids by implementing the DMPC strategy and the DDA strategy, respectively without considering the real-time power compensation stage operation.

Microgrid 1 purchases 4.1696×10^4 kWh electric power from the utility company, sells 100.447 kWh electric power back to the utility company, charges 1.3842×10^3 kWh electric power into the ESD unit, discharges 1.238×10^3 kWh electric power from the ESD unit, and curtails 4.0911×10^3 kWh load power demand in the flexible loads with the DMPC strategy. There is 4.2804×10^4 kWh electric power is purchased from the utility company, 1.5318 kWh electric power is sold back to the utility company, 1.7663×10^3 kWh electric power is charged into the ESD unit, 1.607×10^3 kWh electric power is discharged from the ESD unit, and 104.0521 kWh load power demand is curtailed in the flexible loads with the DDA strategy. The final ESD energy level at the end of the simulation for DMPC strategy and DDA strategy are 169.457 kWh and 144 kWh, respectively. Though less power is purchased from the utility and more power is sold back to the utility with the DMPC strategy than the DDA strategy, the ESD unit plays a more important role with the DMPC strategy than the DDA strategy, moreover, much more flexible power is curtailed with the DMPC strategy than the DDA strategy. Therefore, the operation cost of microgrid 1 with the DMPC strategy is higher than the DDA strategy, as shown in Table VI.

Microgrid 2 purchases 3.4277×10^4 kWh electric power from the utility company, sells 11.18 kWh electric power back to the utility company, charges 1.5522×10^3 kWh electric power into the ESD unit, discharges 1.3915×10^3 kWh electric power from the ESD unit, generates 1.0322×10^4 kWh electric power from the DDG unit, and curtails 1.8871×10^3 kWh load power demand in the flexible loads with the DMPC strategy. There is 3.6445×10^4 kWh electric power is purchased from the utility company, no electric power is sold back to the utility company, 1.6582×10^3 kWh electric power is charged into the ESD unit, 1.5085×10^3 kWh electric power is discharged from the ESD unit, 8.4204×10^3 kWh electric power is generated from the DDG unit, and no flexible load is curtailed in the flexible loads with the DDA strategy. The final ESD energy level at the end of the simulation for DMPC strategy and DDA strategy are 157.4584 kWh and 135 kWh,

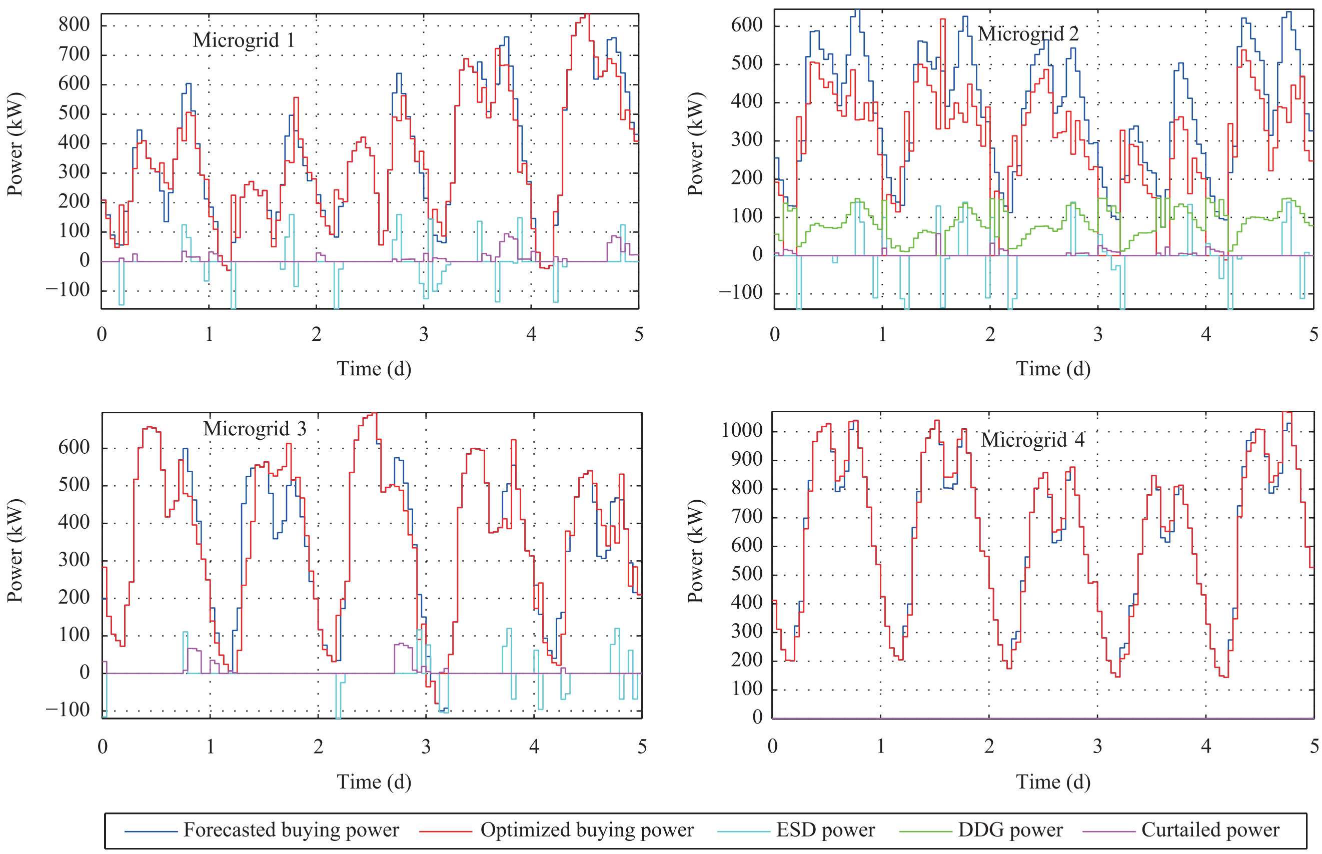

Fig. 3. Operation schedules of the EI system for the DMPC approach.

respectively. The situation of microgrid 2 is similar to microgrid 1, though the DDG unit plays a more important role with the DMPC strategy than the DDA strategy, much more flexible load is curtailed with the DMPC strategy than the DDA strategy, it leads the total operation cost with the DMPC strategy is higher than the DDA strategy.

Microgrid 3 purchases 4.2527×10^4 kWh electric power from the utility company, sells 136.05 kWh electric power back to the utility company, charges 0.8931×10^3 kWh electric power into the ESD unit, discharges 0.8161×10^3 kWh electric power from the ESD unit, and curtails 2.821×10^3 kWh load power demand in the flexible loads with the DMPC strategy. There is 4.3178×10^4 kWh electric power is purchased from the utility company, 98.3384 kWh electric power is sold back to the utility company, 1.3071×10^3 kWh electric power is charged into the ESD unit, 1.4371×10^3 kWh electric power is discharged from the ESD unit, and no flexible load is curtailed in the flexible loads with the DDA strategy. The final ESD energy level at the end of the simulation for DMPC strategy and DDA strategy both are 117 kWh. The situation of micro-grid 3 is similar to microgrid 1, and thus the total operation cost with the DMPC strategy is higher than the DDA strategy.

Microgrid 4 purchases 7.5811×10^4 kWh and 7.5712×10^4 kWh electric power from the utility company for the DMPC strategy and DDA strategy, respectively. No flexible load is curtailed in the flexible loads both with the DMPC strategy and DDA strategy. Therefore, the total operation costs of microgrid 4 with the DMPC strategy and DDA strategy are nearly the same. The reason the total operation costs with the DMPC strategy is a little higher than the DDA strategy is that the forecasts used for the DMPC strategy is updating as the time going, and is more accurate than those used for the DDA strategy.

Meanwhile, we also can evaluate the performance of the above operation strategies by analyzing the power output of the utility company under these strategies. There are 2.0627×10^5 kWh and 1.9431×10^5 kWh electric power generated by the utility without and with considering the DMPC optimization strategy, and $2.0636\ \times10^5$ kWh and 1.9814×10^5 kWh electric power generated by the utility without and with considering the DDA optimization strategy, respectively. The electric power generated by the utility without considering optimization strategies are different in two conditions just due to the forecast model in the DMPC strategy is updated all the time whereas it is no update in the DDA strategy.

As we all know, the forecasts of the RERs products and load demand are imperfect, therefore, the conclusions obtained from the above must be modified according to the actual data. The utility generation in the scheduling stage and the real-time stage with the DMPC strategy is nearly the same, only 263.09 kWh electric power is generated by the fast responsive generators. However, the utility generation in the scheduling stage and the real-time stage with the DDA strategy has a little larger gap than that of the DMPC strategy, there is 5.051×10^3 kWh electric power generated by the fast responsive generators, as shown in Fig. 5. The similar conclusions can also be deduced from Table VI. Though the actual operation costs of the microgrids in the EI system is lower than the costs of condition that no optimization strategy is implemented, the cost increment of the DDA strategy from the scheduling stage to the

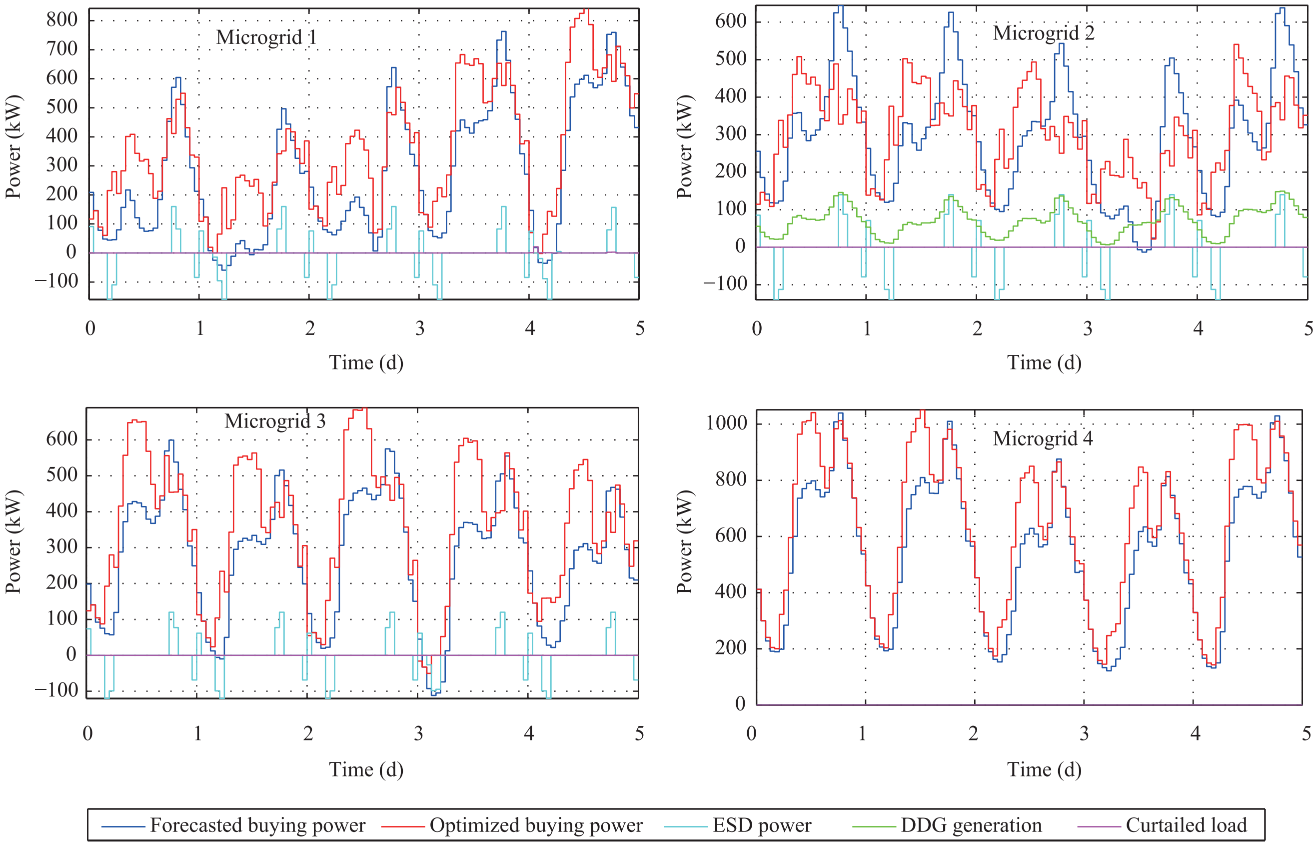

Fig. 4. Operation schedules of the EI system for DDA approach.

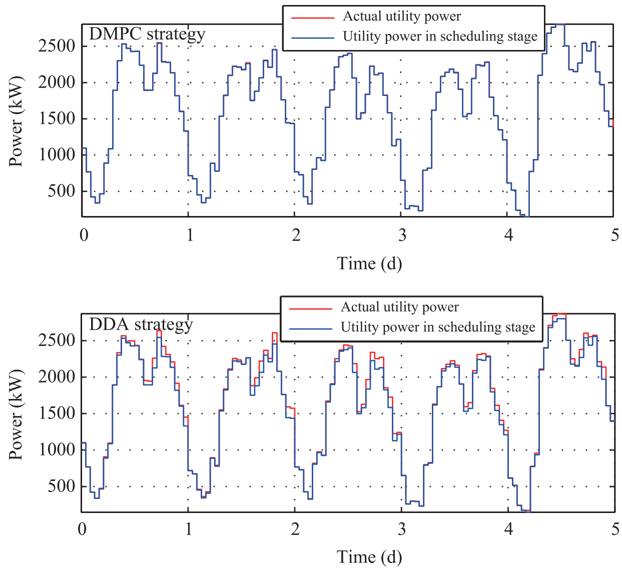

Fig. 5. Actual generation of the utility company with DDA approach and DMPC approach.

TABLE VI
Scheduling Costs and the Total Costs for Both DMPC Approach and DDA Approach

Cost ($\times 10^5$ \$)	Microgrid 1	Microgrid 2	Microgrid 3	Microgrid 4
Scheduling cost with no optimization	0.6661	0.6721	0.6716	1.1479
Scheduling cost with DDA	0.6316	0.5741	0.6376	1.0982
Scheduling cost with DMPC	0.6484	0.5867	0.6537	1.0993
Total cost with no optimization	0.6764	0.6831	0.6856	1.1619
Total cost with DDA	0.6574	0.6016	0.6717	1.1338
Total cost with DMPC	0.6502	0.5878	0.6555	1.1005

real-time stage is higher than that of the DMPC strategy.

4.2.2 Discussions of Microgrid Elements

In this subsection we will discuss the impacts of the ESD units and DDG units in the EI system.

Without the aid of the ESD units, the microgrids have to sell the surplus power generated by the RERs back to the utility when the electricity price is low, and purchase more power from the utility when the electricity price is high. The operation schedules of the microgrids without ESD units have large differences from those of the microgrid with ESD units. The four microgrids purchase 4.2677×10^4 kWh, 3.4412×10^4 kWh, 4.3333×10^4 kWh and 7.580×10^4 kWh electric power from the utility company, respectively. Except microgrid 4 (it has no ESD unit all the time), all the other microgrids increase the power purchased from the utility. They sell -100.1259 kWh, 0, -355.2156 kWh, 0 electric power back to the utility, respectively. The power sold from microgrid 3 increases a lot. In addition, without the ESD unit, the curtailed flexible loads decrease a lot for all the microgrids. Meanwhile, due to the ESD unit is very small, the cost increment for all the microgrids is not very vast, as shown in Table VII.

TABLE VII
SCHEDULING COSTS AND TOTAL COSTS FOR DMPC APPROACH WITHOUT SOME DISPATCHABLE ELEMENTS

Cost ($\times 10^5$\$)	Microgrid 1	Microgrid 2	Microgrid 3	Microgrid 4
Scheduling cost without ESDs	0.6522	0.5920	0.6617	1.1186
Total cost without ESDs	0.6536	0.5929	0.6631	1.1201
Scheduling cost without ESDs and DDG	0.6800	0.6961	0.6846	1.1617
Total cost without ESDs and DDG	0.6788	0.6951	0.6831	1.1605

Though only microgrid 2 has a DDG unit, it also has significant impacts for the other microgrids' operations. The four microgrids purchase 4.2692×10^4 kWh, 4.4706×10^4 kWh, 4.3341×10^4 kWh and 7.5806×10^4 kWh electric power from the utility company, respectively. Only microgrid 2 purchases a large power from the utility, the total purchased power for the other microgrids is nearly the same as the conditions of only without ESD units. Meanwhile, the sold power for all the microgrids are all the same as the conditions of only without ESD units. This simulation case fully illustrates that the microgrids in the EI system are coordinated with each other, though only the DDG unit in microgrid 2 is lost, the operation costs of all microgrids vary a lot.

4.2.3 Discussion of the Step-size Coefficient π

We have briefly discussed the importance of the step-size parameter for the convergence of the parallel distribution optimization algorithm in section III. In this section we will show a series of numerical simulations with different choice of this parameter, as shown in Fig. 6. We

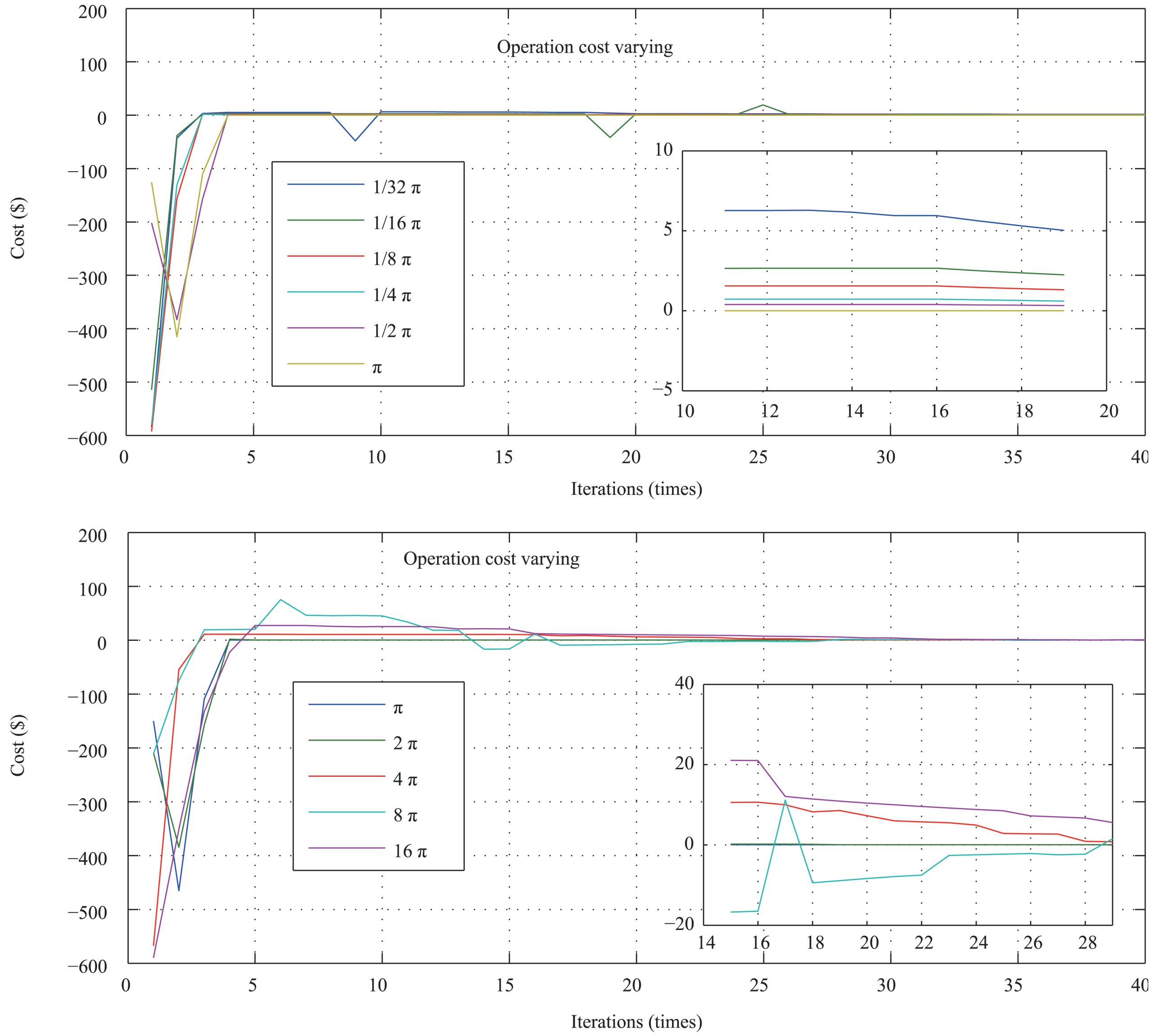

Fig. 6. Convergence of the distributed optimization algorithm with different step-size coefficients.

select the base $\pi = 1$ as used in (33) and then perform a series of simulations with the parameter $\pi_{\rm sim}$ selected as $1/32\pi$, $1/16\pi$, $1/8\pi$, $1/4\pi$, $1/2\pi$, π, 2π, 4π, 8π, and 16π. We observe that for this four microgrids EI system, the convergence of the algorithm proposed in this paper can be achieved in as few as 5 iterations for the base π=1, and the number of iterations depends on the select value $\pi_{\rm sim}$. 6 iteration needed to achieve convergence when $\pi_{\rm sim} = 1/4\pi$. However, if $\pi_{\rm sim}$ becomes too small, the iteration numbers will increase sharply, 22 iterations when $\pi_{\rm sim} = 1/8\pi$, and more than 50 iterations are needed if $\pi_{\rm sim} \leq 1/16\pi$.

5 Conclusion

In this paper, we introduce a MPC-based parallel distributed optimization method for optimal operation of an EI which includes several microgrids, consumers, and a utility company. These microgrids are equipped with critical loads, flexible loads, schedulable loads, wind turbines, PV panels, ESD units, and DDG units, and they are controlled and optimized by their own EMSs. EMS of a microgrid can determine the power purchasing and selling schedule between the microgrid and the utility, the operation plan of the DDG units, ESD units, flexible loads and schedulable loads based on the electricity price information from the EI operator. In order to achieve the coordination of the microgrids and protect the user' privacies, a parallel distributed optimization is proposed, and a soft constraint on the EMS schedule change between two consecutive iterations is added. A traditional DDA strategy is implemented to evaluate the performance of proposed DMPC strategy. Numerical results showed that our proposed strategy is cost saving and robust. The total electricity bill for the microgrids is 2.994 $\times 10^5$ \$ for the DMPC strategy which is less than the 3.0645$\times 10^5$ \$ for the DDA strategy and much less than 3.207 $\times 10^5$ \$ for the normal operation without any optimization. Moreover, the cost increments of the DMPC strategy are the lowest in the three methods when we consider forecast errors, as shown in Table I. The effects of ESD units and DDG units on the DMPC strategy are investigated. Simulation results show that the dispatchable units can reduce the users' electricity bill effectively, and the usage of these units in one microgrid can also affect the operation schedule of other microgrids. The discussion of the step-size coefficient π shows that the step-size coefficient plays an important role for the convergence of the distributed optimization operation method, we can use a small coefficient at the beginning of iteration to accelerate the convergence speed, and use a large coefficient to guarantee the convergence of the distributed optimization method.

In our future work, we will focus on analyzing the EI system optimization operation method where the microgrids can determine the selling and purchasing energy prices, and theoretically analyze the convergence properties of the distributed optimization operation method.

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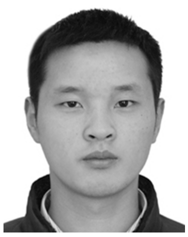

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