Frontiers of Information Technology & Electronic Engineering
www.jzus.zju.edu.cn; engineering.cae.cn; www.springerlink.com
ISSN 2095-9184 (print); ISSN 2095-9230 (online)
E-mail: jzus@zju.edu.cn

Energy management for multi-microgrid system based on model predictive control*

Ke-yong HU[†1,2], Wen-juan LI[1], Li-dong WANG[1], Shi-hua CAO[1], Fang-ming ZHU[3], Zhou-xiang SHOU[1]

[1]*Qianjiang College, Hangzhou Normal University, Hangzhou 310018, China*

[2]*MOE Key Laboratory of Special Purpose Equipment and Advanced Manufacturing Technology, Zhejiang University of Technology, Hangzhou 310014, China*

[3]*School of Information Science and Engineering, Hangzhou Normal University, Hangzhou 311121, China*

[†]E-mail: hukeyong@yeah.net

Received Dec. 17, 2016; Revision accepted Apr. 17, 2017; Crosschecked Nov. 27, 2018

Abstract: To reduce the computation complexity of the optimization algorithm used in energy management of a multi-microgrid system, an energy optimization management method based on model predictive control is presented. The idea of decomposition and coordination is adopted to achieve the balance between power supply and user demand, and the power supply cost is minimized by coordinating surplus energy in the multi-microgrid system. The energy management model and energy optimization problem are established according to the power flow characteristics of microgrids. A dual decomposition approach is imposed to decompose the optimization problem into two parts, and a distributed predictive control algorithm based on global optimization is introduced to achieve the optimal solution by iteration and coordination. The proposed method has been verified by simulation, and simulation results show that the proposed method provides the demanded energy to consumers in real time, and improves renewable energy efficiency. In addition, the proposed algorithm has been compared with the particle swarm optimization (PSO) algorithm. The results show that compared with PSO, the proposed method has better performance, faster convergence, and significantly higher efficiency.

Key words: Microgrids; Energy management; Predictive control; Renewable energy; Controllable energy
https://doi.org/10.1631/FITEE.1601826 **CLC number:** TP273

1 Introduction

Because of the rapid development of microgrid (MG) technology, microgrids are increasingly constructed and connected to distributed networks in the form of smart grids (Lasseter, 2011; Bie et al., 2012; Saad et al., 2012). The local area of a distributed network can contain many microgrids connected to a multi-microgrid system (Yuen et al., 2011; Nunna and Doolla, 2012). In a muli-microgrid system, it is generally assumed that the power dispatch of microgrids must pass through the power network, and a single microgrid is considered as a controlled distributed energy resource (DER). A central energy management system (CEMS) is needed for each microgrid in a power transmission network. A CEMS has many features, such as day-ahead scheduling (DAS) integrated with a real-time scheduling (RTS) unit, and a local energy market (LEM) structure based on the single side auction (SSA) that regulates a real-time energy price. However, due to the development of the communication and signal processing technology, a microgrid can be regarded as an intelligent node, having many microgrids that can reduce the constraints in a power

* Project supported by the National Natural Science Foundation of China (No. 61702151), the First Group of Teaching Reform Research Project in the 13th Five-Year Plan of Higher Education of Zhejiang Province, China (No. jg20180509), the Natural Science Foundation of Zhejiang Province, China (Nos. LY17E070004, LY17F010010, LY19F020022 and LQ14F020008), and the Public Welfare Technology Application Research Project of Zhejiang Province, China (No. 2017C33219)

ORCID: Ke-yong HU, http://orcid.org/0000-0002-8963-6237

transmission network. The adjacent microgrids can exchange energy directly, which is the key reason for the development of the multi-microgrid system and smart grids. Accordingly, the multi-microgrid system has become a hot research topic.

In recent years, there have been many studies on energy management of the multi-microgrid system. Sortomme and El-Sharkawi (2009) proposed the particle swarm optimization (PSO) algorithm to optimize power flow among microgrids and peak power reduction from the economic perspective. Nunna and Doolla (2013) proposed a two-layer energy management structure based on the multi-agent technology to bid for the multi-microgrid and power market. Wei et al. (2014) designed a cooperative game method for a multi-microgrid system in a given region to minimize the losses in power transmission between microgrids. However, the existing incentive methods use only the electricity price and load curve, rather than an electricity pricing mechanism for the direct purpose of peak clipping and valley filling. Therefore, it is impossible to fully characterize the peak clipping and valley filling.

In addition, home microgrids (H-MGs) are very important for transmitting functional parts of a smart grid on a local scale (Alharbi and Raahemifar, 2015; Balasubramaniam et al., 2016). Although the idea of H-MGs is similar to the traditional power system, the main difference is that H-MGs have to be fully capable of autonomous operation in the islanded mode (Marzband et al., 2016a, 2017). Since H-MGs might have a shortage or excess in power generation in the islanded mode, an energy management system (EMS) is needed. In addition, EMSs can adapt and compensate for any change in generation type or capacity and storage assets in real time. Furthermore, EMSs maximize the operational efficiency, which minimizes the operational cost and emission (Tenfen and Finardi, 2015), maximizes the lifetime of assets (Marzband et al., 2016b, 2016d), and increases the reliability of inter-operability and the above-mentioned combination of multi-objective type EMS (Marzband et al., 2014, 2016c). Marzband et al. (2013) developed a new CEMS design according to stability analysis to obtain the best purchasing price in the day-ahead market, and maximize the use of the existing DER. The above-mentioned studies are useful in the development of multi-microgrid systems.

In the past few years, model predictive control (MPC) has been applied to the power system community because of its excellent ability to predict system's future behavior (Kassem and Abdelaziz, 2014; Jiang et al., 2015; Pahasa and Ngamroo, 2016). Nevertheless, there is little literature on the use of MPC to study energy management in the multi-microgrid system. In addition, to reduce the computational complexity of optimization algorithms (Sortomme and El-Sharkawi, 2009), the idea of decomposition and coordination is proposed to achieve a balance between power supply and user demand. Furthermore, the power supply cost is minimized by coordinating the surplus energy in a multi-microgrid system.

The abbreviations used in this study are given in Table 1. The contributions of this study are as follows:

1. The idea of decomposition and coordination is introduced to achieve a balance between power supply and user demand.

2. An intelligent algorithm based on the distributed predictive control is developed to support real-time applications.

3. The energy optimization problem is presented in the form of a state space equation of the multi-microgrid system.

Table 1 Abbreviations used in the paper

Abbreviation	Full name
MG	Microgrid
H-MG	Home microgrid
DER	Distributed energy resource
CEMS	Central energy management system
DAS	Day-ahead scheduling
RTS	Real-time scheduling
LEM	Local energy market
SSA	Single side auction
MPC	Model predictive control
EMS	Energy management system
EMS-MPC	Energy management system of model predictive control
EMS-PSO	Energy management system of particle swarm optimization

2 Framework of a multi-microgrid system

Effective energy management can provide an optimal and sustainable supply of energy with maximum efficiency. Because of the intermittent nature of renewable energy resources, an EMS is needed to find the best solution to supply to consumers quickly and continuously. The multi-microgrid system is composed of several microgrids that can operate independently. The power supply of a multi-microgrid system can be from renewable energy sources, such as solar radiation and wind, or controllable energy sources, such as a gas turbine. Each microgrid in a multi-microgrid system can work in both standalone and interconnection modes (Katiraei and Iravani, 2006; Khorsandi et al., 2016). Therefore, an EMS is required for receiving current and predicted values of customer load and power generation to impose appropriate information on power flow (Mahmood et al., 2015; Rahbar et al., 2015). The information flow and EMS functions in a microgrid are shown in Fig. 1.

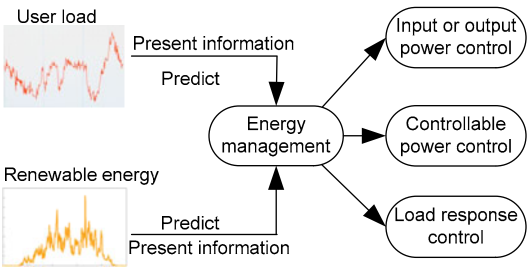

Fig. 1 Information flow and functions of an energy management system (EMS) in a microgrid

In the standalone mode, the supply and demand balance of a microgrid is regulated by the microgrid itself. When the power supply from renewable energy sources is insufficient, an internal controllable power supply is used as a supplement. When the power supply from renewable energy sources is sufficient, the excess power is stored. It is generally assumed that controllable energy supply has a higher economic cost than renewable energy supply (Moghaddam et al., 2011; Vasiljevska et al., 2012). In the interconnection mode, if there is a surplus in renewable energy supply of the microgrid after meeting its own load, the excess energy will be given to microgrids in the adjacent area. Thus, the power generation of controllable energy sources can be greatly decreased.

The structure of a multi-microgrid system in the interconnection mode is shown in Fig. 2. The distributed power supply, user load, and EMS are integrated in microgrids. The control information and state information are exchanged between microgrids by communication lines, and the power transmission is completed by power lines. Therefore, the multi-microgrid system can be regarded as a system composed of many subsystems, which are in correlation and coupled.

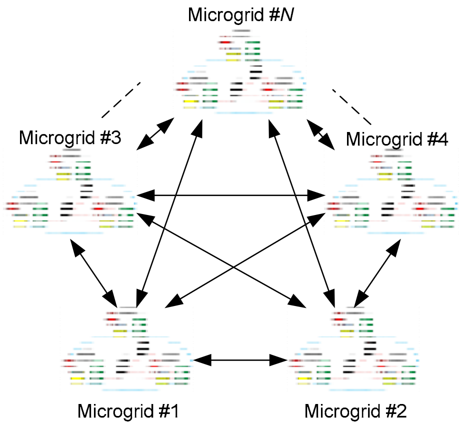

Fig. 2 Structure of a multi-microgrid system in the interconnection mode

3 Energy management model of a multi-microgrid system

3.1 System modeling

In general, a multi-microgrid system model consists of N microgrids, where each microgrid contains renewable energy sources like solar and wind, and a controllable energy source like a gas turbine. In this study, because of the low cost of renewable energy sources, the power transmission among microgrids is based on the transmission of surplus energy generated by renewable energy sources.

To clearly describe the multi-microgrid system, the following variables are defined:

1. $P_i^{\text{renew}}(k)$ denotes the supply from renewable energy sources in the i^{th} (i=1, 2, …, N) microgrid at time k. Although the power supply from renewable energy sources is random and intermittent, according to historical data, it can use the existing prediction methods to estimate future output power.

2. $P_i^{\text{ref}}(k)$ represents the demand power of the i^{th} microgrid generated by the user load at time k. According to historical data, it can estimate future electricity demand by existing prediction methods.

3. $u_i(k)$ is the power supply from controllable energy sources in the i^{th} microgrid at time k.

4. $a_{ij}\in(0, 1)$ is the ratio of power flows of the i^{th}

to j^{th} (j=1, 2, …, N, $j\neq i$) microgrids at time k. The value is affected by the distance between microgrids, electricity demand, and other factors. In addition, $\sum a_{ij}\leq 1$.

5. $b_{ii}\in[0, 1]$ denotes the ratio of the power supply generated by controllable energy sources to all the power supply in the i^{th} microgrid at time k.

At time k, if the i^{th} microgrid is unable to meet its own load demand by its own renewable energy sources, defined as

$$P_i^{\text{renew}}(k)-P_i^{\text{ref}}(k)<0, \tag{1}$$

the objective function is set to minimize the gap between the power supply and demand of user load:

$$\min\|P_i^{\text{renew}}(k)-P_i^{\text{ref}}(k)\|. \tag{2}$$

There are two ways to reduce the gap between the power supply and demand:

1. The power scheduling of the i^{th} microgrid might obtain the power flow of surplus renewable energy from the j^{th} ($j\neq i$) microgrid nearby:

$$a_{ij}(P_j^{\text{renew}}(k)-P_j^{\text{ref}}(k)). \tag{3}$$

2. The power supply of the i^{th} microgrid can be generated by its own controllable energy sources:

$$b_{ii}u_i(k). \tag{4}$$

Thus, the energy management model of the multi-microgrid system can be expressed as

$$\begin{gathered}\boldsymbol{P}^{\text{renew}}(k+1)-\boldsymbol{P}^{\text{ref}}(k+1)=\boldsymbol{A}(\boldsymbol{P}^{\text{renew}}(k)-\boldsymbol{P}^{\text{ref}}(k))\\ +\boldsymbol{Bu}(k),\\ \boldsymbol{A}=\begin{bmatrix}a_{11} & a_{12} & \cdots & a_{1N}\\ a_{21} & a_{22} & \cdots & a_{2N}\\ \vdots & \vdots & & \vdots\\ a_{N1} & a_{N2} & \cdots & a_{NN}\end{bmatrix},\boldsymbol{B}=\begin{bmatrix}b_{11} & 0 & \cdots & 0\\ 0 & b_{22} & \cdots & 0\\ \vdots & \vdots & & \vdots\\ 0 & 0 & \cdots & b_{NN}\end{bmatrix},\end{gathered} \tag{5}$$

where $\boldsymbol{P}^{\text{renew}}(k)-\boldsymbol{P}^{\text{ref}}(k)=[P_1^{\text{renew}}(k)-P_1^{\text{ref}}(k), P_2^{\text{renew}}(k)-P_2^{\text{ref}}(k), \ldots, P_N^{\text{renew}}(k)-P_N^{\text{ref}}(k)]^{\text{T}}$ and $\boldsymbol{u}(k)=[u_1(k), u_2(k), \ldots, u_N(k)]^{\text{T}}$.

If $\boldsymbol{P}^{\text{renew}}(k)-\boldsymbol{P}^{\text{ref}}(k)$ is set to be equal to the state variable of the multi-microgrid system, the state variable space of the system can be expressed as

$$\boldsymbol{x}(k)=[x_1(k), x_2(k), \cdots x_N(k)]^{\text{T}}. \tag{6}$$

Thus, the energy management model of the multi-microgrid system is transformed into the form of state variable space:

$$\boldsymbol{x}(k+1)=\boldsymbol{Ax}(k)+\boldsymbol{Bu}(k). \tag{7}$$

To achieve energy management of the multi-microgrid system, the balance between the power supply and demand of each microgrid should be ensured, and the use of controllable energy sources of higher cost should be reduced. Accordingly, the energy management optimization of the multi-microgrid system is defined as

$$\min(\|\boldsymbol{x}(k+1)\|^2+\|\boldsymbol{u}(k)\|^2). \tag{8}$$

3.2 Model decomposition

The multi-microgrid system represents a high-dimensional, nonlinear, strong coupling, and dynamic system. To facilitate computation, the energy management model is decomposed based on the dual decomposition principle, which is easy to realize in the distributed control of microgrids.

The energy influence value of the i^{th} microgrid from other microgrids in a multi-microgrid system at time k is

$$v_i(k)=\sum_{j=1, j\neq i}^{N}a_{ij}x_j(k). \tag{9}$$

Substituting Eq. (9) into Eq. (7), the model is separated into two interconnected subsystems. Thus, the original model can be transformed into the following form:

$$x_i(k+1)=a_{ii}x_i(k)+b_{ii}u_i(k)+v_i(k). \tag{10}$$

After model decomposition, the energy optimization problem can be considered from the prediction time domain and control time domain.

4 Energy prediction model of the multi-microgrid system

In the prediction time domain P and control time domain M ($M \subseteq P$), the predictive model can be expressed as

$$\boldsymbol{X}_i(k+1)=\boldsymbol{A}_i\boldsymbol{X}_i(k)+\boldsymbol{B}_i\boldsymbol{U}_i(k)+\boldsymbol{A}_{ij}\boldsymbol{V}_i(k), \quad (11)$$

where $\boldsymbol{U}_i(k)$ is the power supply matrix of the i^{th} microgrid generated by its own controllable energy sources. $\boldsymbol{U}_i(k)=[u_i(k|k), u_i(k+1|k), \ldots, u_i(k+M-1|k)]^{\text{T}}$, where $u_i(k+T|k)$ ($T=0, 1, \ldots, M-1$) denotes the power supply generated by its own controllable energy sources at time $k+T$ predicted using the present power supply of the i^{th} microgrid at time k and the historical data. $\boldsymbol{X}_i(k+1)$ is the difference matrix between the power supply and demand of the i^{th} microgrid. Here, the power supply originates from renewable energy sources of the microgrid, and the power demand originates from the electrical consumption of the user load. Thus, the difference matrix is described as $\boldsymbol{X}_i(k+1)=[x_i(k+1|k), x_i(k+2|k), \ldots, x_i(k+P|k)]^{\text{T}}$, where $x_i(k+T|k)$ ($T=1, 2, \ldots, P$) represents the difference between the power supply and user demand of the i^{th} microgrid from time k to time $k+T$, and it is predicted using the difference between the power supply generated by renewable energy sources of the i^{th} microgrid and the electrical consumption by user load at time $k+T$. $\boldsymbol{V}_i(k)$ is the influenced energy matrix of the i^{th} microgrid, which is affected by other microgrids. $\boldsymbol{V}_i(k)=[v_i(k|k), v_i(k+1|k), \ldots, v_i(k+P-1|k)]^{\text{T}}$, where $v_i(k+T|k)$ ($T=0, 1, \ldots, P-1$) represents the influenced data of the i^{th} microgrid from time k to time $k+T$, and it is predicted using the influenced value of the i^{th} microgrid from other microgrids at time $k+T$.

Consequently, the corresponding state matrix and control matrix are as follows:

$$\begin{gathered}\boldsymbol{A}_i=\begin{bmatrix} a_{ii} \\ a_{ii}^2 \\ \vdots \\ a_{ii}^P \end{bmatrix},\ \boldsymbol{A}_{ij}=\begin{bmatrix} a_{ij} & 0 & \cdots & 0 \\ a_{ii}a_{ij} & a_{ij} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ a_{ii}^{P-1}a_{ij} & a_{ii}^{P-2}a_{ij} & \cdots & 0 \end{bmatrix}, \\ \boldsymbol{B}_i=\begin{bmatrix} b_{ii} & 0 & \cdots & 0 \\ a_{ii}b_{ii} & b_{ii} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ a_{ii}^{P-1}b_{ii} & a_{ii}^{P-2}b_{ii} & \cdots & a_{ii}^{P-M}b_{ii} \end{bmatrix}.\end{gathered} \quad (12)$$

To improve the use of renewable energy sources and reduce the need for controllable energy sources, the energy optimization goal of the system model is defined as

$$\min \boldsymbol{J}(k)=\min_{\boldsymbol{U}_i(k)}\sum_{i=1}^{N}(\|\boldsymbol{X}_i(k+1)\|^2+\|\boldsymbol{U}_i(k)\|^2). \quad (13)$$

The energy optimization problem can be considered in both the prediction and control time domains. In the following section, the distributed predictive control algorithm is improved to achieve the optimal solution.

5 Distributed predictive control algorithm

The predictive control algorithm represents a discrete control algorithm based on the feedback. It considers only the predictive function of the controlled object model, without the consideration of the model form. The function of the prediction model is based on the historical information of controlled object and the future input information $\{\boldsymbol{u}(k|k), \boldsymbol{u}(k+1|k), \ldots, \boldsymbol{u}(k+M-1|k)\}$, and they are used to predict the future output information $\{\boldsymbol{x}(k+1|k), \boldsymbol{x}(k+2|k), \ldots, \boldsymbol{x}(k+P|k)\}$. This feature is more suitable for dealing with the complex computing problem faced by multi-microgrid energy optimization, and the basic structure of the predictive control is shown in Fig. 3.

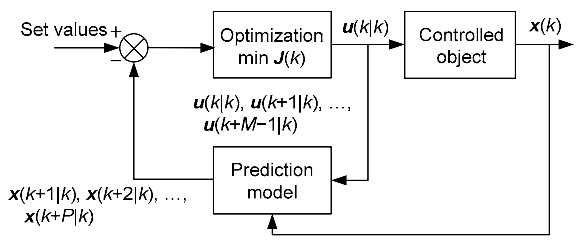

Fig. 3 Structure of the predictive control model

Since the multi-microgrid system contains N microgrids, the state space equation of the multi-microgrid system can be expressed as

$$\begin{cases} \boldsymbol{x}(k+1)=\boldsymbol{A}\boldsymbol{x}(k)+\boldsymbol{B}\boldsymbol{u}(k), \\ \boldsymbol{y}(k)=\boldsymbol{C}\boldsymbol{x}(k). \end{cases} \quad (14)$$

Using the predictive time domain P and control time domain M, the future state variable and control variable are as follows:

$$\begin{cases} \boldsymbol{x}(k+1\,|\,k),\ \boldsymbol{x}(k+2\,|\,k),\ \cdots,\ \boldsymbol{x}(k+P\,|\,k), \\ \boldsymbol{u}(k\,|\,k),\ \boldsymbol{u}(k+1\,|\,k),\ \cdots,\ \boldsymbol{u}(k+M-1\,|\,k), \end{cases} \tag{15}$$

where $\boldsymbol{x}(k+P|k)$ represents the state information at time k. In the prediction model, this state information can be used to predict the state information at time $k+P$:

$$\boldsymbol{x}(k+P\,|\,k)=\boldsymbol{A}^P\boldsymbol{x}(k)+\sum_{j=0}^{M-1}\boldsymbol{A}^{P-j-1}\boldsymbol{B}\boldsymbol{u}(k+j). \tag{16}$$

Thus, the forecasting output is described as

$$\boldsymbol{y}(k+P\,|\,k)=\boldsymbol{C}\boldsymbol{A}^P\boldsymbol{x}(k)+\sum_{j=0}^{M-1}\boldsymbol{C}\boldsymbol{A}^{P-j-1}\boldsymbol{B}\boldsymbol{u}(k+j). \tag{17}$$

If the new vectors are defined as

$$\boldsymbol{Y}=[\boldsymbol{y}(k+1\,|\,k)^{\mathrm{T}},\boldsymbol{y}(k+2\,|\,k)^{\mathrm{T}},\cdots,\boldsymbol{y}(k+P\,|\,k)^{\mathrm{T}}]^{\mathrm{T}}, \tag{18}$$

$$\boldsymbol{U}=[\boldsymbol{u}(k\,|\,k)^{\mathrm{T}},\boldsymbol{u}(k+1\,|\,k)^{\mathrm{T}},\cdots,\boldsymbol{u}(k+M-1\,|\,k)^{\mathrm{T}}]^{\mathrm{T}}, \tag{19}$$

then it can be written as

$$\boldsymbol{Y}=\boldsymbol{\Phi}\boldsymbol{x}(k)+\boldsymbol{\Psi}\boldsymbol{U}, \tag{20}$$

where

$$\boldsymbol{\Phi}=\begin{bmatrix} \boldsymbol{CA} \\ \boldsymbol{CA}^2 \\ \vdots \\ \boldsymbol{CA}^P \end{bmatrix},\ \boldsymbol{\Psi}=\begin{bmatrix} \boldsymbol{CB} & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{CAB} & \boldsymbol{CB} & \cdots & \boldsymbol{0} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{CA}^{P-1}\boldsymbol{B} & \boldsymbol{CA}^{P-2}\boldsymbol{B} & \cdots & \boldsymbol{CA}^{P-M}\boldsymbol{B} \end{bmatrix}. \tag{21}$$

Consequently, the output of the multi-microgrid system at the next time moment is

$$\boldsymbol{Y}(k+j)=f[\boldsymbol{Y}_0(k),\boldsymbol{u}_1(k),\boldsymbol{u}_2(k),\cdots,\boldsymbol{u}_N(k)], \tag{22}$$

where j=1, 2, …, P, $\boldsymbol{u}_i(k)$ is the N-dimensional input vector, $\boldsymbol{Y}(k+j)$ and $\boldsymbol{Y}_0(k)$ are the output of the predictive value and the initial predictive value at time k, respectively, and f is the mapping function. Meanwhile, the input and output variables should meet the constraint conditions:

$$\boldsymbol{u}_{\min}\le\boldsymbol{u}(\cdot)\le\boldsymbol{u}_{\max}, \tag{23}$$

$$\boldsymbol{Y}_{\min}\le\boldsymbol{Y}(\cdot)\le\boldsymbol{Y}_{\max}. \tag{24}$$

Hence, the optimization goal (13) of the multi-microgrid system is transformed into

$$\min_{\boldsymbol{u}_1(k),\cdots\boldsymbol{u}_N(k)}\boldsymbol{J}=\min\left\{\sum_{j=1}^{P}\boldsymbol{L}[\boldsymbol{Y}(k+j\,|\,k),\boldsymbol{u}_1(k),\boldsymbol{u}_2(k)\cdots,\boldsymbol{u}_N(k)]\right\}. \tag{25}$$

In microgrid optimization, the coupling of microgrids must be considered. Thus, the prediction equation of the i^{th} microgrid is defined as

$$y_i(k)=f_i[y_{i,0}(k),\ u_1(k),\ u_2(k),\ \cdots,\ u_N(k)]. \tag{26}$$

The traditional distributed control structure requires the assignment of optimization indices to various regulators of microgrids (Scattolini, 2009) (Fig. 4).

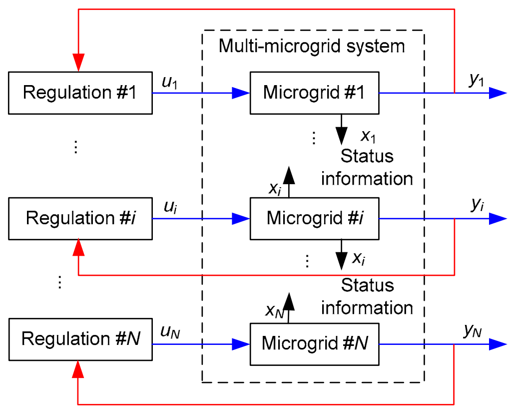

Fig. 4 Traditional distributed control structure

Accordingly, the global optimization index of the multi-microgrid system represents a simple sum of all microgrid optimization indices. For the i^{th} microgrid, the optimization index in the predictive control algorithm based on the Nash optimization is expressed as

$$J_i=\sum_{j=1}^{P}L_i[y_i(k+j\,|\,k),\ u_{i,M}(k)]. \tag{27}$$

The Nash equilibrium is composed of the optimal strategy of each microgrid, but it does not mean that it is the optimal result of a system. The optimization of each microgrid is just one part of global system optimization. When the local optimization index of each microgrid is in conflict with the global optimization index of the system, the output result is difficult to converge to the optimal solution of the whole control system.

The redesign of the distributed control structure based on global optimization (Fig. 5) should consider both the local optimization index of each microgrid and the influenced index of the whole multi-microgrid system. The control sequences of microgrids related to the i^{th} microgrid have to be added to the control law of the i^{th} microgrid.

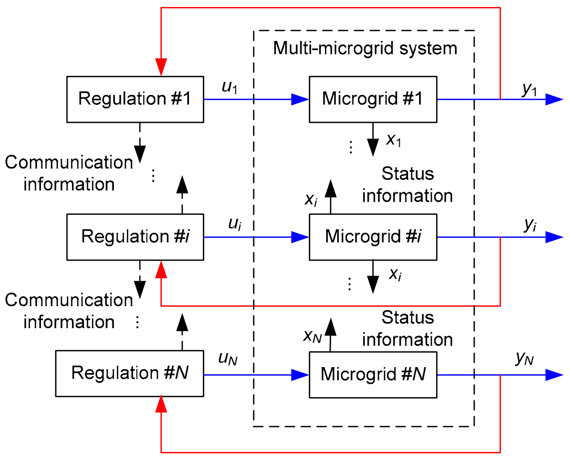

Fig. 5 Distributed control structure based on global optimization

Thus, at time k and after the $(l+1)^{\text{th}}$ iteration, the optimization index of the i^{th} microgrid is obtained:

$$\min_{u_i^{l+1}(k)} J_i(k) = L_i[y_i^{l+1}(k),\ u_i^{l+1}(k),\ u_j^l(k)] + \sum_{j=1, j\neq i}^{N} L_j[y_j^{l+1}(k),\ u_i^{l+1}(k),\ u_g^l(k)], \tag{28}$$

where j, g=1, 2, …, N, $j\neq i$, and $g\neq i$. The first part on the right side of Eq. (28) represents the local optimization index of the i^{th} microgrid, and the second part the influenced index of the i^{th} microgrid in the global optimization process. $y_i^{l+1}(k)$ and $y_j^{l+1}(k)$ are obtained from the following prediction equations:

$$y_i^{l+1}(k) = f_i[y_{i,0}(k),\ u_i^{l+1}(k),\ u_j^l(k)], \tag{29}$$

$$y_j^{l+1}(k) = f_j[y_{j,0}(k),\ u_j^{l+1}(k),\ u_g^l(k)]. \tag{30}$$

The workflow of the proposed algorithm is shown in Fig. 6, and its realization is as follows:

1. At time k, the number of iterations is set to l=0, and the initial forecasting value of the i^{th} microgrid $y_{i,0}(k)$ is provided to other microgrids. The i^{th} microgrid obtains the information flow about the initial forecasting values of other microgrids $y_{j,0}(k)$ ($j\neq i$). Thus, the initial control value $u_{i,0}(k)$ is provided to each microgrid.

2. Each microgrid obtains the information flow about previous control sequences of other microgrids. Based on the optimization index (Eq. (28)) and predictions (Eqs. (29) and (30)), the optimal solution of this iteration $u_i^{l+1}(k)$ is obtained.

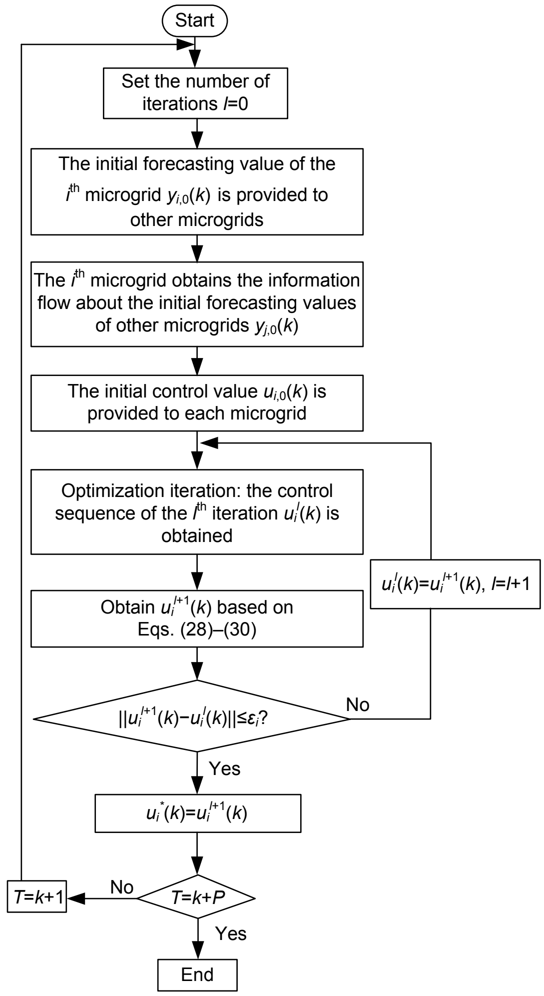

Fig. 6 Workflow of the proposed algorithm

3. The accuracy is set to ε_i to determine whether the predictive iteration is convergent for each microgrid, or in other words, whether the inequality $\|u_i^{l+1}(k)-u_i^l(k)\|\le\varepsilon_i$ is satisfied. If the iterations of microgrids are all convergent, the iterations are stopped. The control law $u_i^*(k)$ obtains the final solution $u_i^*(k)=u_i^{l+1}(k)$ and the algorithm goes to the next step. Otherwise, $u_i^l(k)=u_i^{l+1}(k)$, $l=l+1$, and the algorithm returns to the previous step.

4. The control law $u_i^*(k)$ that satisfies the iterative convergence is used as the optimal control law at time k and applied to the operation of each microgrid.

5. Time is shifted to time k+1, and the algorithm returns to step 1. The above process is repeated until time k+P when all the predictive control operations are ended.

To provide a better understanding of the proposed idea and the sequence of steps, a high-level flowchart of the proposed algorithm is shown in Fig. 7.

The operation and management of each MG in different modes can be controlled by the local EMS at the primary-level. An MPC is embedded in the second-level and it is responsible for the overall coordination of these EMSs. It collects operation information of MGs and allocates power exchange between MGs.

6 Simulation results

To verify the proposed control idea, a three-microgrid system has been established. Each microgrid contains solar and energy sources, a gas turbine, and a user load. Microgrids are interconnected as shown in Fig. 8. The distance between microgrid #1 and microgrid #2 is the shortest, while the distance between microgrid #1 and microgrid #3 is the longest.

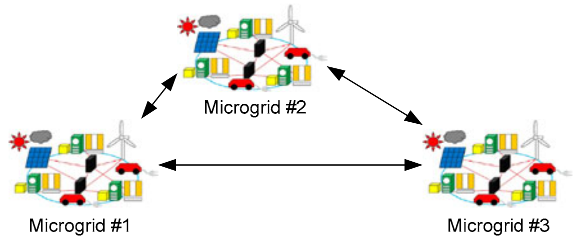

Fig. 8 Position relation of three microgrids

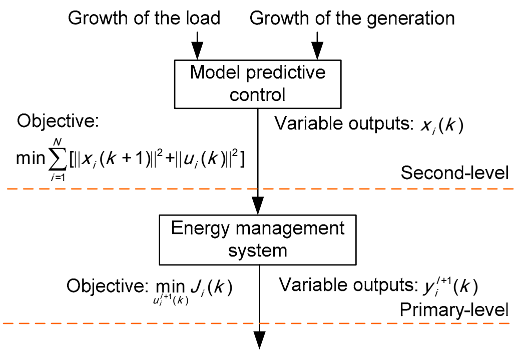

Fig. 7 High-level flowchart of the proposed algorithm where *i*=1, 2, …, *N*

It is assumed that the operation mode of each microgrid is the same. First, the microgrid uses the power from its own renewable energy sources, e.g. solar and wind energy. If there is extra power generated by renewable energy sources after meeting the microgrid's own load, it is transferred to the nearest microgrid. However, if the power generated by all renewable energy sources in the multi-microgrid system is unable to meet the user load, the controllable energy sources will be employed. The renewable energy sources have a lower cost than controllable energy sources.

According to the operational characteristics of each microgrid, artificial data of microgrids are shown in Fig. 9 with the time step for calculation of 5 min. To set the working environment, the following assumptions are made: the power supply of microgrid #1 originates mainly from solar energy, and the peak power consumption is concentrated from 7:00 to 8:00 in the morning and from 18:00 to 20:00 in the evening. These are typical characteristics of a residential district. The power supply of microgrid #2 originates mainly from solar and wind energy, and the peak power consumption is concentrated in working hours, from 9:00 to 11:00 in the morning and from 13:00 to 17:00 in the afternoon. These are typical characteristics of a working district. The power supply of microgrid #3 originates mainly from wind energy, and the peak power consumption is concentrated from 6:00 to 12:00 in the morning. These are typical characteristics of a farming district. The microgrids of the three different types are interconnected into the multi-microgrid system.

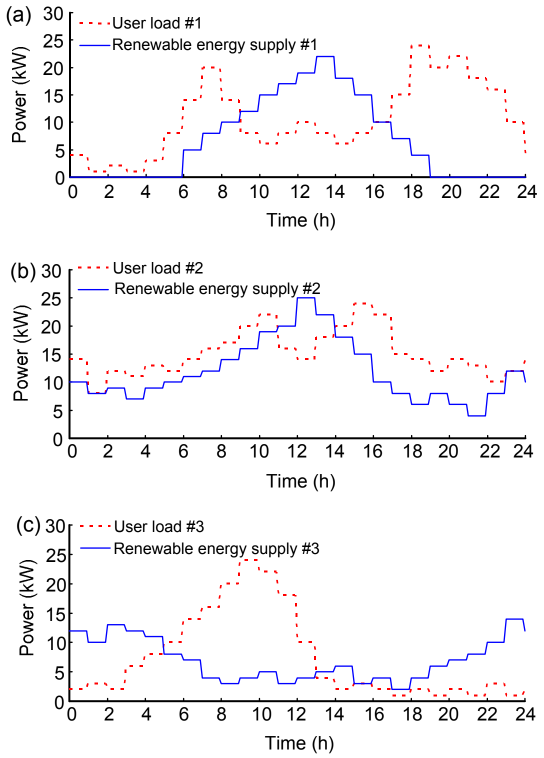

Fig. 9 Curves of renewable energy supply and user load of microgrids #1 (a), #2 (b), and #3 (c)

Clearly, if microgrids run independently, there is no cooperation between them. Sometimes, when the power supply from renewable energy sources cannot meet its own user load, the power consumption is supplemented by only controllable energy sources. Accordingly, since the surplus renewable power of microgrids cannot be transmitted between microgrids, the renewable energy utilization is very low. However, if the energy management model of the multi-microgrid system is adopted considering the power flow between microgrids, the system model parameters are set as follows:

$$\boldsymbol{x}(k+1)=\begin{bmatrix}0.3 & 0.5 & 0.2\\ 0.5 & 0.2 & 0.3\\ 0.2 & 0.3 & 0.5\end{bmatrix}\boldsymbol{x}(k)+\begin{bmatrix}0.6 & 0 & 0\\ 0 & 0.8 & 0\\ 0 & 0 & 0.1\end{bmatrix}\boldsymbol{u}(k), \tag{31}$$

where $\boldsymbol{x}(k)=[x_1(k), x_2(k), x_3(k)]^{\mathrm{T}}$ and $\boldsymbol{u}(k)=[u_1(k), u_2(k), u_3(k)]^{\mathrm{T}}$.

The controllable power supply curves of each microgrid on a daily basis in both independent (no collaboration) and interconnected (with collaboration) conditions are shown in Fig. 10. Under the premise that a microgrid can meet real-time user demand by itself, the controllable power supply data of each microgrid in the two operating conditions are used for comparison. Namely, microgrids #1, #2, and #3 have reduced the use of the controllable energy supply by 17%, 58%, and 26%, respectively. In other words, when the energy management model is applied to the multi-microgrid system working in the interconnected mode, the dependence on the controllable energy can be decreased greatly and the validity of the control strategy of the multi-microgrid system has been confirmed.

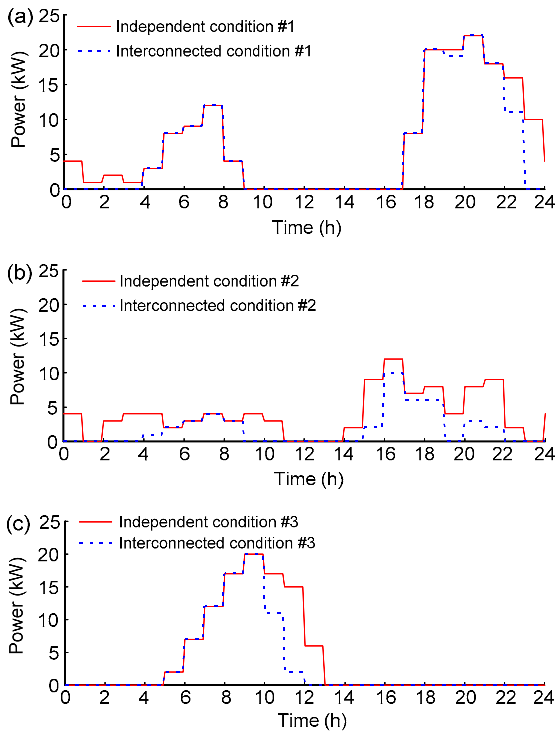

Fig. 10 Curves of the controllable power supply in independent and interconnected conditions of microgrids #1 (a), #2 (b), and #3 (c)

Since the energy management of a multi-microgrid system represents a complex multi-dimensional computation, the proposed algorithm has been applied to the prediction control model. The parameters of the algorithm were set as follows: the prediction time domain P and control time domain M were equal, $P=M=8$, and the objective precision was set to $\varepsilon_i=0.7$ ($i=1, 2, 3$). Simulation results are shown in Fig. 11.

In Fig. 11, the solid and dotted lines represent the actual power supply and the predictive power supply of microgrids #1, #2, and #3 on daily basis, respectively. The actual power supply of each microgrid is consistent with the predictive value. Namely, microgrid #1, which belongs to the residential area, gave the surplus electricity generated from its own renewable energy sources to microgrid #2 during the period of 9:00–11:00 in the morning, which was the peak period of power consumption of microgrid #2. Thus, the real-time power supply of microgrid #2, which belongs to the working area, was guaranteed. The same situation occurred during the period of 14:00–17:00. The surplus power originated from renewable energy sources of microgrids #1 and #3 was transmitted to microgrid #2, which greatly reduced the use of controllable energy sources of microgrid #2 in this period.

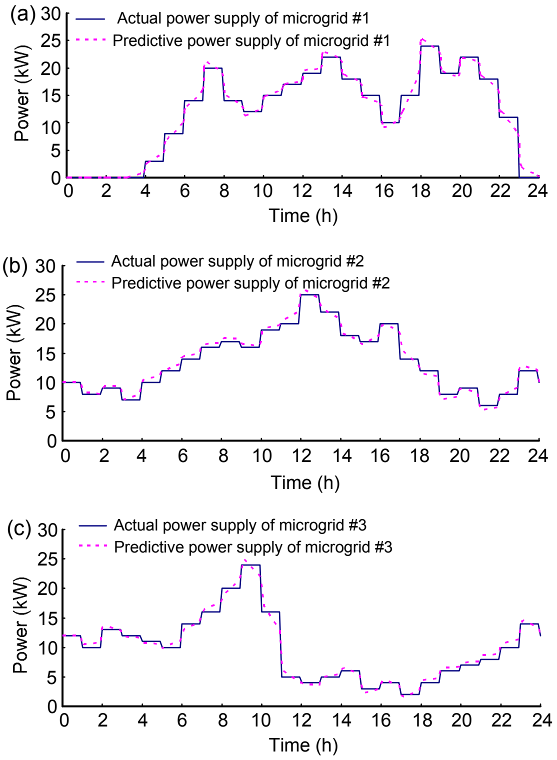

Fig. 11 Actual power supply and predictive values of microgrids #1 (a), #2 (b), and #3 (c)

Hence, it can be concluded that the proposed algorithm can use the system's inherent capability and provide collaboration between microgrids. The algorithm can effectively estimate the real-time power supply of each microgrid and give a powerful decision-making basis for optimal dispatch of power flow.

The proposed algorithm has been verified by an EMS in the C programming environment on a computer with a 3.4-GHz CPU and a 4-GB RAM. In comparison, the execution time of the CPU for algorithms MPC and PSO was presented in Table 2. The results show that the CPU allocates less time to the execution of EMS-MPC than that of EMS-PSO.

Table 2 Average calculation time of the system with different algorithms

Algorithm	Execution time (s)
EMS-PSO	2.1
EMS-MPC	1.6

In addition, the convergence specification of the proposed algorithm has been analyzed and compared to that of PSO. The iteration times of the proposed and PSO algorithms are shown in Fig. 12. The maximum number of iterations is set to 40. The proposed algorithm converged after 23 iterations while the PSO algorithm converged after 31 iterations. The results show that EMS-MPC requires less computation than EMS-PSO.

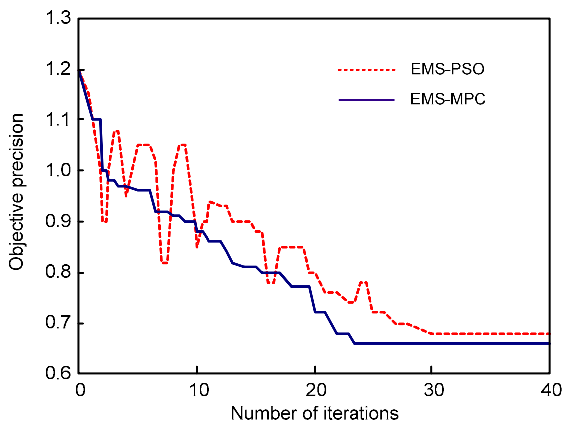

Fig. 12 Characteristics of convergence

7 Conclusions

In this study, an energy optimization management algorithm has been proposed based on the model predictive control to reduce the computation complexity of an optimization algorithm. The idea of decomposition and coordination has been proposed to achieve the balance between the power supply and user demand, and the cost of the power supply has been minimized by coordination of the surplus energy in the multi-microgrid system. The approach decomposes the optimization problem into two parts, and a distributed predictive control algorithm based on the global optimization was improved to achieve the optimal solutions by iteration and coordination.

The results proved the effectiveness of the proposed method, which can provide demanded energy to consumers in real time and improve the renewable energy efficiency. The performance of the proposed algorithm has been compared with that of a PSO algorithm, and results showed that the convergence speed of the proposed algorithm was increased and a remarkable improvement of efficiency was achieved.

We are currently considering the extension of this study to the distributed control scheme, wherein the microgrids exchange information flow with neighbors according to a certain rule. This control scheme can greatly reduce the need for a central processor. However, the improvement of reliability and robustness of the control method has become a thorny problem, and it will be one of our future research topics.

References

Alharbi W, Raahemifar K, 2015. Probabilistic coordination of microgrid energy resources operation considering uncertainties. *Electr Power Syst Res*, 128:1-10. https://doi.org/10.1016/j.epsr.2015.06.010

Balasubramaniam K, Saraf P, Hadidi R, et al., 2016. Energy management system for enhanced resiliency of microgrids during islanded operation. *Electr Power Syst Res*, 137:133-141. https://doi.org/10.1016/j.epsr.2016.04.006

Bie ZH, Zhang P, Li GF, et al., 2012. Reliability evaluation of active distribution systems including microgrids. *IEEE Trans Power Syst*, 27(4):2342-2350. https://doi.org/10.1109/tpwrs.2012.2202695

Jiang H, Lin J, Song YH, et al., 2015. MPC-based frequency control with demand-side participation: a case study in an isolated wind-aluminum power system. *IEEE Trans Power Syst*, 30(6):3327-3337. https://doi.org/10.1109/tpwrs.2014.2375918

Kassem AM, Abdelaziz AY, 2014. Reactive power control for voltage stability of standalone hybrid wind-diesel power system based on functional model predictive control. *IET Renew Power Gener*, 8(8):887-899. https://doi.org/10.1049/iet-rpg.2013.0199

Katiraei F, Iravani MR, 2006. Power management strategies for a microgrid with multiple distributed generation units. *IEEE Trans Power Syst*, 21(4):1821-1831. https://doi.org/10.1109/tpwrs.2006.879260

Khorsandi A, Ashourloo M, Mokhtari H, et al., 2016. Automatic droop control for a low voltage DC microgrid. *IET Gener Transm Distrib*, 10(1):41-47. https://doi.org/10.1049/iet-gtd.2014.1228

Lasseter RH, 2011. Smart distribution: coupled microgrids. *Proc IEEE*, 99(6):1074-1082. https://doi.org/10.1109/jproc.2011.2114630

Mahmood H, Michaelson D, Jiang J, 2015. Accurate reactive power sharing in an islanded microgrid using adaptive virtual impedances. *IEEE Trans Power Electron*, 30(3): 1605-1617. https://doi.org/10.1109/tpel.2014.2314721

Marzband M, Sumper A, Ruiz-Álvarez A, et al., 2013. Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets. *Appl Energy*, 106:365-376. https://doi.org/10.1016/j.apenergy.2013.02.018

Marzband M, Ghadimi M, Sumper A, et al., 2014. Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for microgrids in islanded mode. *Appl Energy*, 128:164-174. https://doi.org/10.1016/j.apenergy.2014.04.056

Marzband M, Parhizi N, Savaghebi M, et al., 2016a. Distributed smart decision-making for a multimicrogrid system based on a hierarchical interactive architecture. *IEEE Trans Energy Conv*, 31(2):637-648. https://doi.org/10.1109/tec.2015.2505358

Marzband M, Javadi M, Domínguez-García JL, et al., 2016b. Non-cooperative game theory based energy management systems for energy district in the retail market considering DER uncertainties. *IET Gener Transm Distrib*, 10(12): 2999-3009. https://doi.org/10.1049/iet-gtd.2016.0024

Marzband M, Parhizi N, Adabi J, 2016c. Optimal energy management for stand-alone microgrids based on multi-period imperialist competition algorithm considering uncertainties: experimental validation. *Int Trans Electr Energy Syst*, 26(6):1358-1372. https://doi.org/10.1002/etep.2154

Marzband M, Yousefnejad E, Sumper A, et al., 2016d. Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization. *Int J Electr Power Energy Syst*, 75:265-274. https://doi.org/10.1016/j.ijepes.2015.09.010

Marzband M, Ghazimirsaeid SS, Uppal H, et al., 2017. A real-time evaluation of energy management systems for smart hybrid home Microgrids. *Electr Power Syst Res*, 143:624-633. https://doi.org/10.1016/j.epsr.2016.10.054

Moghaddam AA, Seifi A, Niknam T, et al., 2011. Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy*, 36(11):6490-6507. https://doi.org/10.1016/j.energy.2011.09.017

Nunna HSVSK, Doolla S, 2012. Demand response in smart distribution system with multiple microgrids. *IEEE Trans*

Smart Grid, 3(4):1641-1649.
https://doi.org/10.1109/tsg.2012.2208658

Nunna HSVSK, Doolla S, 2013. Multiagent-based distributed-energy-resource management for intelligent microgrids. *IEEE Trans Ind Electron*, 60(4):1678-1687.
https://doi.org/10.1109/tie.2012.2193857

Pahasa J, Ngamroo I, 2016. Coordinated control of wind turbine blade pitch angle and PHEVs using MPCs for load frequency control of microgrid. *IEEE Syst J*, 10(1):97-105. https://doi.org/10.1109/jsyst.2014.2313810

Rahbar K, Xu J, Zhang R, 2015. Real-time energy storage management for renewable integration in microgrid: an off-line optimization approach. *IEEE Trans Smart Grid*, 6(1):124-134. https://doi.org/10.1109/tsg.2014.2359004

Saad W, Han Z, Poor HV, et al., 2012. Game-theoretic methods for the smart grid: an overview of microgrid systems, demand-side management, and smart grid communications. *IEEE Signal Process Mag*, 29(5):86-105.
https://doi.org/10.1109/msp.2012.2186410

Scattolini R, 2009. Architectures for distributed and hierarchical model predictive control—a review. *J Process Contr*, 19(5):723-731.
https://doi.org/10.1016/j.jprocont.2009.02.003

Sortomme E, El-Sharkawi MA, 2009. Optimal power flow for a system of microgrids with controllable loads and battery storage. IEEE/PES Power Systems Conf and Exposition, p.1-5. https://doi.org/10.1109/psce.2009.4840050

Tenfen D, Finardi EC, 2015. A mixed integer linear programming model for the energy management problem of microgrids. *Electr Power Syst Res*, 122:19-28.
https://doi.org/10.1016/j.epsr.2014.12.019

Vasiljevska J, Lopes JAP, Matos MA, 2012. Evaluating the impacts of the multi-microgrid concept using multicriteria decision aid. *Electr Power Syst Res*, 91:44-51.
https://doi.org/10.1016/j.epsr.2012.04.013

Wei C, Fadlullah ZM, Kato N, et al., 2014. GT-CFS: a game theoretic coalition formulation strategy for reducing power loss in micro grids. *IEEE Trans Parall Distrib Syst*, 25(9):2307-2317.
https://doi.org/10.1109/tpds.2013.178

Yuen C, Oudalov A, Timbus A, 2011. The provision of frequency control reserves from multiple microgrids. *IEEE Trans Ind Electron*, 58(1):173-183.
https://doi.org/10.1109/tie.2010.2041139