FREQUENCY $H_2/H_\infty$ OPTIMIZING CONTROL FOR ISOLATED MICROGRID BASED ON IPSO ALGORITHM

ZHONG-QIANG WU* AND XI-BO ZHAO

Key Lab of Industrial Computer Control Engineering of Hebei Province
College of Electric Engineering
Yanshan University, Qinhuangdao 066004, China

(Communicated by Changzhi Wu)

Abstract. Affected by the fluctuation of wind and load, large frequency change will occur in independently islanded wind-diesel complementary microgrid. In order to suppress disturbance and ensure the normal operation of microgrid, a $H_2/H_\infty$ controller optimized by improved particle swarm algorithm is designed to control the frequency of microgrid. $H_2/H_\infty$ hybrid control can well balance the robustness and the performance of system. Particle swarm algorithm is improved. Adaptive method is used to adjust the inertia weight, and cloud fuzzy deduction is used to determine the learning factor. Improved particle swarm algorithm can solve the problem of local extremum, so the global optimal goal can be achieved. It is used to optimize $H_2/H_\infty$ controller, so as to overcome the conservative property of solution by linear matrix inequality and improve the adaptive ability of controller. Simulation results show that with a $H_2/H_\infty$ controller optimized by improved particle swarm algorithm, the frequency fluctuations caused by the wind and load is decreased, and the safety and stable operation of microgrid is guaranteed.

1. Introduction. Isolated microgrid is a kind of microgrid which has independent operation function so it can operate with the utility grid, also can operate independently [14]. Microgrid can solve the power supply in remote areas, somewhere the disaster of utility grid occurring and for military in case of war, so it has important strategic significance [31, 15]. The voltage and frequency stability of microgrid are important to ensure the normal operation of microgrid [9]. Because the capacity and inertia of microgrid itself are small, the uncertain load and wind can cause the output power of microgrid has the characteristic such as random, intermittent and volatile [26, 16], which will lead to the active power imbalance of microgrid, and cause the substantial fluctuation of frequency, even beyond the safe and stable operation range of microgrid. Therefore, when wind and other uncertainty factors come into the microgrid, in order to guarantee the safe and stable operation of microgrid, an appropriate frequency control strategy must be adopted.

In recent years, the significant results have been achieved to suppress the frequency deviation of microgrid by reducing the output power of new energy and using control methods. In reference [19], load shedding strategy is used to control...
the frequency of microgrid when the frequency is low. In reference [23], the frequency of isolated microgrid is modulated secondly by main frequency modulator, the quality of power is improved, and the influence of frequency deviation to the charge-discharge of energy storage device is avoided, at the same time the condition which microgrid connects to utility grid is built. In reference [8], decentralized control strategy (DCS) is used to control the frequency of microgrid, and the stability of the microgrid is improved. In reference [4], a virtual inertia frequency control strategy is used, and it makes the microgrid have drooping characteristics, also similar to the rotor inertia of synchronous generator at the same time. When there are disturbances, the strategy can support the frequency of microgrid, so the frequency stability of microgrid is improved. In reference [18], the energy storage device is introduced and limited load operation is used to control the frequency of microgrid. In reference [20], the installed energy storage device is used to stabilize the frequency and voltage of microgrid. In reference [17], a PID controller with genetic algorithm is used to inhibit the disturbance and frequency deviation of microgrid. In reference [27], Hamiltonian modeling of multi-hydro-turbine governing systems with sharing common penstock is used to nonlinear dynamic analyses under shock load. In reference [28], Dynamic analysis and modeling is adopted for a novel fractional order hydro turbine generator unit. In reference [25], the modeling of the fractional-order shafting system for a water jet mixed-flow pump during the startup process has been researched. In reference [3], Hamiltonian model and dynamic analyses is used for a hydro-turbine governing system with fractional item and time-lag. In reference [11], Hamiltonian analysis is adopted to a hydro-energy generation system in the transient of sudden load increasing.

According to statement above microgrid is a system with strong random disturbances. In the condition of ensuring the performance of system, the key of microgrid normal operation is to maximize suppress system disturbances. When there are disturbances, the problem of linear quadratic optimal control can be converted into $H_2$ control [30, 24]. Good dynamic performance can be got by $H_2$ control, but it lacks robustness to disturbances. However $H_\infty$ control has robustness to disturbances based on sacrificing the other performance of the system. The combination of two controls can better take into account the robustness and the performance of system. For independent wind-diesel microgrid, a hybrid $H_2/H_\infty$ frequency control strategy based on IPSOImproved Particle Swarm Optimizationalgorithm is proposed. In order to reduce the frequency fluctuations of microgrid caused by wind and load, secondary frequency control is added, in the meantime a hybrid $H_2/H_\infty$ controller is designed to make the system has strong robustness to wind and load, so good control performance is ensured. IPSO algorithm is used to optimize $H_2/H_\infty$ controller, the conservative property of LMI solution is overcome, the adaptive ability of controller is improved, the problem of falling into local optimum can be avoided, and the global optimization is achieved. Simulation results show that $H_2/H_\infty$ controller optimized by IPSO algorithm can better take into account the robustness and performance of system, and global optimization is achieved. The frequency deviation of microgrid is controlled within the required range, and the safe and stable operation of micro-grid is ensured.

2. The structure of independent wind-diesel microgrid. For many remote mountainous area and small islands away from the mainland, due to the geographical conditions and natural environment, large power grid is difficult to overall
coverage. However these remote areas often have unique natural advantages such as abundant wind, solar and so on. So microgrid is very suitable for these areas. Micropower sources include wind generator, photovoltaic cell, and diesel generator etc. They can form a variety of microgrids. Such as wind-diesel complementary microgrid, wind-photovoltaic complementary microgrid, wind-photovoltaic-diesel complementary microgrid etc. Wind energy has the characteristics of no pollution, recycled, and has become an indispensable new energy in modern generation industry. Due to the restriction of the weather conditions, wind power can cause large frequency deviation and voltage fluctuation for microgrid. The traditional way to deal with this problem is that the large energy storage devices such as capacity are used to improve the quality of power. The disadvantage is that it increases the operation cost of microgrid, and causes secondary pollution in later process for energy storage devices.

In order to solve the problems above and optimize the power quality of microgrid, diesel generator is used to instead of the energy storage devices to form independent wind-diesel complementary microgrid. Diesel generator has the advantages such as high efficiency, low maintenance, flexible operation, high security and reliability. So the wind-diesel complementary microgrid is adopted facilitating to improve the control effect. For the frequency deviation of microgrid caused by the randomness of wind and load, diesel generators is used as secondary frequency modulator to correct frequency deviation, and the stable operation of the microgrid is ensured. The independent wind-diesel microgrid is shown in Fig.1.

![Figure 1. Independent wind-diesel microgrid](image)

The dynamic model of microgrid is shown in Fig.2. It includes diesel generator, wind turbine, load and controller. In the control strategy proposed, the traditional maximum power tracking control is adopted for the wind power generation system. In Fig.2, $\Delta f$ is frequency deviation; $P_G$ is the power output of diesel generator; $X_G$ is the position increment of governor valve; $E$ is the integral control increment; $P_w$ is wind power; $P_L$ is load; $T_G$ is the speed time constant; $T_T$ is the time constant of diesel generator; $T_P$ is the time constant of power system; $K_p$ is the relevant gain; $R$ is the speed adjustment coefficient of governor; $K_E$ is the integral control gain, $u$ is the control input.

3. **The mathematical model of independent microgrid.** The mathematical model of independent microgrid in figure 2 can be expressed as
Figure 2. The dynamic model of microgrid

\[
\begin{align*}
\Delta f &= -\frac{1}{T_p} \Delta f + K_p \frac{P_G}{T_p} - \frac{K_p}{T_p} (P_d - P_w) \\
P_G &= -\frac{1}{T_p} P_G + \frac{1}{T_p} X_G \\
X_G &= -\frac{1}{RT_G} \Delta f - \frac{1}{T_G} X_G - \frac{1}{T_G} E + \frac{1}{T_G} u \\
\dot{E} &= KE \Delta f 
\end{align*}
\]

Equation (1) can be further written as matrix form:

\[
\begin{align*}
\dot{x} &= A_1 x + B_1 u + H_1 (P_d - P_w) \\
y &= Cx 
\end{align*}
\]

where \( x = [\Delta f, P_G, X_G, E]^T \),

\[
A_1 = \\
\begin{bmatrix}
-1/T_p & K_p/T_p & 0 & 0 \\
0 & -1/T_T & 1/T_T & 0 \\
-1/RT_G & 0 & -1/T_G & -1/T_G \\
K_E & 0 & 0 & 0
\end{bmatrix}
\]

\[
B_1 = [0, 0, 1/T_G, 0]^T, \ C = [1, 0, 0, 0], \ H_1 = [-K_p/T_p, 0, 0, 0]^T, \ y = \Delta f.
\]

Equation (2) is discretized into equation (3)

\[
\begin{align*}
x(k+1) &= A_1 x(k) + B_1 u(k) + H_1 (P_d(k) - P_w(k)) \\
y(k) &= Cx(k)
\end{align*}
\]

where \( A = e^{A_1 T} \), \( B = \int_0^T e^{A_1 T} dt \cdot B_1 \), \( H = \int_0^T e^{A_1 T} dt \cdot H_1 \), \( T \) is the sampling period, \( k \) is the number of iterations. After define the evaluation signal, system (3) can be written as:

\[
\begin{align*}
x(k+1) &= A_c x(k) + B_1 u(k) + H_1 (P_d(k) - P_w(k)) \\
y(k) &= Cx(k) \\
z_2(k) &= Cx(k) + Du(k) \\
z_\infty &= Cx(k)
\end{align*}
\]

where \( z_2(k) \in R \) is evaluation signal relevant with \( H_2 \), \( z_\infty(k) \in R \) is evaluation signal relevant with \( H_\infty \), \( D = 1 \).

Let \( u(k) = Kx(k) \) and the closed loop system is:

\[
\begin{align*}
x(k+1) &= A_c x(k) + H_1 (P_d(k) - P_w(k)) \\
y(k) &= Cx(k)
\end{align*}
\]

where \( A_c = A + BK \), \( K = [k_1, k_2, k_3, k_4] \).

\[
z_2(k) = [C + DK]x(k)
\]

In reference [10], for a frequency control problem of isolated photovoltaic-diesel hybrid microgrid, load estimator is designed. It is complicated and the accuracy of the control is directly influenced by the accuracy of the estimation. In the paper,
$H_2/H_\infty$ controller is designed, and $H_\infty$ index is used to restrain disturbances, so load estimator is omitted. $H_2$ index is used to get good dynamic performance.

Let $T_2(z, K)$ denotes the closed loop transfer function from $P_1(k) - P_v(k)$ to $z_2(k)$, and $T_\infty(z, K)$ denotes the closed loop transfer function from $P_1(k) - P_v(k)$ to $z_\infty(k)$. The mixed $H_2/H_\infty$ multi-objective optimization control problem can be expressed as: Find an optimal controller $K^*$ to make the objective function

$$J(K) = \min_{K} \| T_2(z, K) \|_2 + \| T_\infty(z, K) \|_\infty$$

the smallest.

Where $\| T_2(z, K) \|_2 = \sqrt{\frac{1}{2\pi} \int_{-\infty}^{\infty} \text{Trace}[T(e^{jw})^H T(e^{jw})] dw}$ and

$$\| T_\infty(z, K) \|_\infty = \max_{\theta \in [0,\pi]} | T(e^{j\theta}) |$$

are $H_2$ and $H_\infty$ norm of linear discrete systems (5) respectively. In this paper, IPSO algorithm is adopted to solve the objective function (7).

4. Solve the objective function based on IPSO algorithm.

4.1. Solve the objective function based on PSO algorithm. PSO algorithm is an evolutionary technology given by Eberhart and Kennedy in 1995 inspired according to the predatory behavior of birds. PSO adapts the sharing information strategy of biological groups, optimizing search through cooperation and competition among particles, so PSO is easy to implement and needs less adjustable parameters. It has been proved that it is a high efficient intelligent optimization algorithm.

Firstly, initializing a group of random particles (random solutions), the quality of the solution is determined by the fitness function, and generally optimized objective function is selected as the fitness function [2]. The fitness function of this paper is given by the objective function (7) as:

$$f = \frac{1}{J}$$

From the unknown variable $K = [k_1, k_2, k_3, k_4]$, it can be seen that the search space is 4-dimension. Let the position and velocity of $i$-th particle as $X_i = (x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4})$ and $V_i = (v_{i,1}, v_{i,2}, v_{i,3}, v_{i,4})$ respectively. The particles update themselves by following the two current optimal solutions. The first one is $p_{\text{best}i} = (p_{\text{best}1}, p_{\text{best}2}, p_{\text{best}3}, p_{\text{best}4})$, which is the optimal solution of the particle itself from the initialization to the current generation of iterations. The second is $g_{\text{best}i} = (g_{\text{best}1}, g_{\text{best}2}, g_{\text{best}3}, g_{\text{best}4})$, which is the optimal solution of all the population of particles produced so far. In the solution space, particles continue to search by following the two optimal solutions, until a predetermined numbers of iteration are reached or a preset operation precision is met. For the $k$-th iteration, particles update their speed and position according to equation (9) and (10).

$$v_{i,j}(k + 1) = w v_{i,j}(k) + c_1 r_1 [p_{\text{best}i,j} - x_{i,j}(k)] + c_2 r_2 [g_{\text{best}j} - x_{i,j}(k)]$$

$$x_{i,j}(k + 1) = x_{i,j}(k) + v_{i,j}(k + 1); j = 1, \ldots, 4$$

where $w$ is inertia weight; $c_1$, $c_2$ are self-learning factor; $r_1$, $r_2$ are the random numbers of interval $[0,1]$.

In the PSO algorithm, the velocity vector is usually limited. When $v_{i,j} > v_{\text{max}}$, let $v_{i,j} = v_{\text{max}}$ when $v_{i,j} < v_{\text{min}}$, let $v_{i,j} = v_{\text{min}}$. PSO algorithm can be summarized as the following steps:
1. Set the relevant parameters $c_1$, $c_2$, $w$, and the numbers of particle $N$, and initial population, randomly generate candidate solution of positions and velocities of particles in groups.

2. Evaluate individual one by one in the population, through calculating the fitness $f_i$ of each particle, so the degree of excellence of the particle is measured.

3. The fitness $f_i$ of each individual compares with the fitness of the best position $p_{best_i}$ itself experienced, if better, it is regarded as the current best position. The fitness compares with the fitness of experienced best position $g_{best}$ in the group, if better, it is regarded as a global best position.

4. According to equation (9) and (10) to calculate the speed and position of each particle at new moment.

5. If the maximum number of iteration $\psi$ or the minimum error precision $\varepsilon$ is met, iteration is over, otherwise, goes to (2).

The flow chart of PSO algorithm is shown in Fig.3.

![Figure 3. Flow chart of PSO algorithm](image)

4.2. Solve the objective function based on IPSO algorithm. PSO algorithm has the advantage of easy implementation, less parameters and so on, but as an evolutionary method, it has the same problem such as slow convergence speed and premature convergence. In reference [6], EDA is used to prevent premature convergence in PSO. In reference [7], distribution particle swarm optimization algorithm is put forward. In reference [22], genetic particle swarm optimization based on estimation of distribution is used. In reference [13], a hybrid particle swarm optimization with estimation of distribution algorithm is adopted. In reference [5], hybrid particle swarm optimization and genetic algorithm is used. In reference [29],
particle swarm optimization is used for a multi-objective problem. In reference [12], comprehensive learning particle swarm optimizer is put forward. In reference [21], a cooperative approach is introduced into particle swarm optimization. In reference [1], the estimation of particle swarm distribution algorithms combining the benefits of PSO and EDAs is achieved.

An IPSO algorithm is proposed in this paper. Adaptive method is used to adjust the inertia weight \( w \), and cloud fuzzy deduce is used to determine the learning factor \( c_1, c_2 \), so as to avoid algorithm falling into local optimal.

The specific steps are as follows.

(1) Due to that the larger \( w \) will help improve the global search ability of the algorithm, while the smaller \( w \) will help enhance the local search ability of the algorithm. Therefore, reasonably selecting \( w \) is conducive to balance the global and local search ability of PSO algorithm. According to the fitness function \( f \), the adaptive control law of can be defined as follows:

\[
w(f) = \frac{1}{1 + 1.5e^{-1.6f}} \in [0.4, 0.9]
\]

(2) \( c_1 \) and \( c_2 \) determine the experience information of particle itself, the impact of experience information among other particles for the running trajectory, and reflect the information exchange among particles. If \( c_1 \) is larger, the particles will faster reach the historical optimal positions of their own; If \( c_2 \) is bigger, particles would premature converge to the global optimal position in current, that is to say it is easy to fall into local optimum. In traditional PSO, \( c_1 \) and \( c_2 \) which are used to update the velocity of particle are fixed, and have nothing to do with the characteristics of particles themselves, therefore, the efficiency is low. In the practical application of PSO algorithm, \( c_1 \) and \( c_2 \) should be adjusted based on the dynamic distances of particles, and it is conducive for particles jumping out of the local optimal value.

Some definitions of distance among the particles are given here.

The distance between the particle \( i \) and \( j \) particle is defined as:

\[
D(i,j) = \sqrt{\sum_{k=1}^{4} (x_{i,k} - x_{j,k})^2 + (f(X_i) - f(X_j))^2}
\]

(12)

Different from the general distance, in (12), the distance of independent variables and the distance of objective function are both taken into account.

The maximum distance of particle swarm is defined as:

\[
MD = MaxD(i, j)
\]

(13)

The average distance of particles in the groups is defined as:

\[
AD = \sum_{i=1}^{N} \sum_{j=1}^{N} D(i, j) / N^2
\]

(14)

The average distance of the particle swarm and the optimal particle is defined as:

\[
AD_{g_{best}} = \sum_{i=1}^{N} D(i, g_{best}) / N
\]

(15)

where \( D(i, g_{best}) \) is the distance of the current particle \( i \) and the global optimal particle \( g_{best} \).
$D(i, g_{\text{best}})$ is used as input, the Cloud fuzzy deduce is used to determine the learning factor $c_1$ and $c_2$, the speed of the particle can be controlled effectively, and the balance between global and local optimum of the algorithm can be achieved.

Cloud model has three digital features: expectation $Ex$, entropy $En$, super entropy $He$, and reflect the quantitative characteristics of the qualitative concept. Expectation $Ex$ can best represent the point value of qualitative concept in number field space, and reflects the gravity center of the cloud droplets; Entropy $En$ reflects the measurable degree of qualitative concept, usually the bigger it is, and the more macroscopical the concept is. It is also the uncertainty measurement of qualitative concept, determined by the randomness and fuzziness of concept. On the one hand, $En$ is the measurement of the qualitative concept, reflecting the discrete degree of qualitative concept, and it is the degree of independence and relatedness, reflecting the scope of cloud droplets which can be accepted by the concept in domain space. Super entropy $He$ is uncertainty measurement of the entropy, determined by the randomness and fuzziness of entropy. Three digital characteristics of the cloud model fully integrate together the fuzziness and randomness of linguistic, and form a mapping relationship between qualitative and quantitative. The cloud membership functions of $D(i, g_{\text{best}})$ is shown in Fig.4.

![Cloud membership function of $D(i, g_{\text{best}})$](image)

In Fig.4, $\alpha$ and $\beta$ represent two numbers in $(0, \text{Max}D(i, g_{\text{best}}))$: $\alpha = \text{Min}\{AD, ADg_{\text{best}}\}$, $\beta = \text{Max}\{AD, ADg_{\text{best}}\}$.

The cloud membership functions of $c_1$ and $c_2$ are shown in Fig.5.

![Cloud membership functions of $c_1$, $c_2$](image)

In Fig.5, $c_{\text{im}}$ is the middle value of $(c_{\text{imin}}, c_{\text{imax}})$, $i = 1, 2$.

Firstly initializing $c_1$ and $c_2$, the fuzzy adjusting rules of $c_1$ and $c_2$ according to $D(i, g_{\text{best}})$ are shown in Table 1.
TABLE 1. The fuzzy rules of $c_1$ and $c_2$

| Rules | $D(i, g_{best})$ | $c_1$ | $c_2$ |
|-------|------------------|-------|-------|
| 1     | Near Small Big   |       |       |
| 2     | Middle Middle Middle |     |       |
| 3     | Far Big Small    |       |       |

5. The simulation research. The parameters of model as follows:

$$A = \begin{bmatrix} -0.065 & 8 & 0 & 0 \\ 0 & -3.663 & 3.663 & 0 \\ -6.86 & 0 & -13.736 & -13.736 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ 13.736 \\ 0 \end{bmatrix}, \quad H = \begin{bmatrix} -8 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$C = [1, 0, 0, 0]$$

Select initial value: $c_1 = 1.4926$, $c_2 = 1.4926$, $w = 0.7298$, $\psi = 1000$, $N = 20$, $\varepsilon = 0.1$. The $H_2/H_\infty$ simulation results are shown in figure 6.10. The solution based on LMI is introduced for comparison. It can be got by the solver feasp in LMI toolbox: $K = [0.6565, -0.2366, 1.5833, 0.5842]$.
6. Conclusion. For isolated wind-diesel complementary microgrid, a new frequency optimization control strategy is put forward. A $H_2/H_\infty$ controller optimized by IPSO algorithm is adopted to stabilize the frequency of microgrid. $H_2/H_\infty$ control can ensure the robustness and the performance of system. PSO algorithm is improved. Adaptive method is used to adjust the inertia weight, and cloud fuzzy deduction is used to determine the learning factor. The problems easy to fall into local optimal can be avoided, and the global optimal is achieved. IPSO algorithm is used to optimize $H_2/H_\infty$ controller, the conservative property of LMI solution is overcome, and the adaptive ability of controller is improved. The simulation results show that, $H_2/H_\infty$ controller optimized by IPSO algorithm has strong robustness and good system performance, and ensures the normal operation of microgrid.
Figure 9. Frequency deviation of microgrid (with $H_2/H_{\infty}$ control based on PSO algorithm)

Figure 10. Frequency deviation of microgrid (with $H_2/H_{\infty}$ control based on IPSO algorithm)

REFERENCES

[1] C. W. Ahn, J. An and J. C. Yoo, Estimation of particle swarm distribution algorithms: Combining the benefits of PSO and EDAs, *Information Sciences*, 192 (2012), 109–119.

[2] H. Baek, J. Ryu and J. Oh, et al., Optimal design of multi-storage network for combined sewer overflow management using a diversity-guided, cyclic-networking particle swarm optimizer-A case study in the Gunja subcatchment area, Korea, *Expert Systems with Applications*, 42 (2015), 6966–6975.

[3] B. Xu, D. Chen and H. Zhang, et al., Hamiltonian model and dynamic analyses for a hydro-turbine governing system with fractional item and time-lag, *Commun Nonlinear Sci Numer Simulat*, 47 (2017), 35–47.

[4] W. Du, Q. Jiang and J. Chen, Frequency Control Strategy of Distributed Generations Based on Virtual Inertia in a Microgrid, *Automation of Electric Power Systems*, 35 (2012), 26–31.

[5] H. Duan, Q. Luo and Y. Shi, et al., Hybrid particle swarm optimization and genetic algorithm for multi-UAV Formation Reconfiguration, *IEEE Computational Intelligence Magazine*, 8 (2013), 16–27.
[6] M. El-Abd, Preventing premature convergence in a PSO and EDA hybrid, *IEEE Congress on Evolutionary Computation*, (2009), 3060–3066.

[7] M. Iqbal and M. A. M. De Oca, An estimation of distribution particle swarm optimization algorithm, *Springer Berlin Heidelberg*, German, 4150 (2006), 72–83.

[8] H. J. Jia, Y. Qi and Y. F. Mu, Frequency response of autonomous microgrid based on family-friendly controllable loads, *Science China Technological Sciences*, 56 (2013), 693–702.

[9] H. Li, B. Fu, C. Yang, B. Zhao and X. Tang, Research on microgrid and its application in China, *Proceedings of the CSEE*, 32 (2012), 24–31.

[10] Y. Mi and C. Wang, Frequency optimization control for isolated photovoltaic-diesel hybrid microgrid based on load estimation, *Proceedings of the CSEE*, 33 (2013), 115–121.

[11] H. Li, D. Chen, H. Zhan, C. Wu and X. Tang, Hamiltonian analysis of a hydro-energy generation system in the transient of sudden load increasing, *Applied Energy*, 185 (2017), 244–253.

[12] J. J. Liang, A. K. Qin and P. N. Suganthan, et al., Comprehensive learning particle swarm optimizer for global optimization of multimodal functions, *IEEE Transactions on Evolutionary Computation*, 10 (2006), 281–295.

[13] H. Liu, L. Gao and Q. Pan, A hybrid particle swarm optimization with estimation of distribution algorithm for solving permutation flowshop scheduling problem, *Expert Systems with Applications*, 38 (2011), 4348–4360.

[14] M. Liu, L. Guo and C. Wang, et al., A coordinated operating control strategy for hybrid isolated microgrid including wind power, photovoltaic system, diesel generator, and battery storage, *Dianxi Xitong Zidonghua(Automation of Electric Power Systems)*, 36 (2012), 19–24.

[15] X. Ma, Y. Wu, H. Fang and Y. Sun, Optimal sizing of hybrid solar-wind distributed generation in an islanded microgrid using improved bacterial foraging algorithm, *Proceedings of the CSEE*, 31 (2012), 17–25.

[16] J. Wang, Genetic particle swarm optimization based on estimation of distribution, *Springer Berlin Heidelberg*, German, 4688 (2007), 287–296.

[17] H. Wang and G. Li, Control strategy of microgrid with different DG types, *Electric Power Automation Equipment*, 32 (2012), 19–23.

[18] B. Xu, F. Wang, D. Chen and H. Zhang, Hamiltonian modeling of multi-hydro-turbine governing systems with sharing common penstock and dynamic analyses under shock load, *High Voltage Apparatus*, 49 (2013), 142–149.

[19] B. Xue, M. Zhang and W. N. Browne, Particle swarm optimization for feature selection in classification: A multi-objective approach, *IEEE Trans Cybern*, 43 (2013), 1656–1671.
[31] Q. Zhang, C. Peng and Y. Chen, et al., A Control Strategy for Parallel Operation of Multi-inverters in Microgrid, *Proceedings of the CSEE*, 32 (2012), 126–132.

Received February 2017; 1st revision June 2017; final revision August 2017.

E-mail address: meuzq@163.com
E-mail address: 1294269301@qq.com