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Improved-PSO-based optimal scheduling for rectifier power system

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Abstract: An optimization problem of series current scheduling for rectifier power system is presented in accordance with the policy of the time-of-use price. Aimed at the nonlinearity and the feature with equality and inequality constraints in this global optimization problem, an improved particle swarm optimization algorithm is proposed. In order to avoid premature convergence to local minimum, the improved particle swarm optimization algorithm adjusts its inertia weight according to the change of population's fitness, and determines its mutation probability depending on the average distance of current population. The algorithm's performance is tested through three typical test function experiments. An optimal scheduling system based on the proposed methods is developed and has been put into use since Jan. 2006. Its industrial running results show its effectiveness, stability and reliability.

1. INTRODUCTION

Electrolysis is the final production process in hydrometallurgical process, where metal ions in electrolyte releases from cathode plate. It consumes a great deal of direct current electrical power. In China, the cost of industrial electric power is charged by the policy of the time-of-use price since 2005. If a hydrometallurgical smelting enterprise consumes less electric power in sharp peak-load period and much in valley-load period, it will make great economical profit with the same consumption of electric power. So, how to optimally schedule the series current of each zinc electrolysis series in different period under the condition of normal production, will not only decreases the cost of electrical power and power consumption significantly, but also benefits to balancing the power grid load.

However, the process of zinc electrolysis (PZE) is very complex, where there are much nonlinearity and uncertain factors [Chunhua Yang(1997)]. These factors influencing the electrical power consumption are very complicated and interact each other. It is difficult to build a mathematical model to describe the relationships among them. In addition, some technological requirements including equality and inequality constraints have to be satisfied to ensure high product quality and normal production. This optimization problem has a typical non-linearity with equality and inequality constraints, along with nondifferentiable neural network process model. It is difficult for traditional methods to solve such an optimization problem.

Different from traditional search algorithms, Particle Swarm Optimization (PSO) is a new evolutionary computation technique based on "Swarm Intelligence" and it was originally designed and developed by Eberhart and Kennedy in 1995[Kennedy J, Eberhart R(1995)]. Especially, unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. These characteristics of PSO enhance its search capability and it can find a near optimum solution quickly. In addition, PSO has more advantages, such as clear concept, effectiveness, relatively easy implementation and computational efficiency and so on. It was widely used in science research and engineering applications including optimal loading of the power system [Amgad (2006)], greenhouse air temperature predictive control [J.P. Coelho (2007)], optimal economic dispatch problem [D.N. Jeyakumar (2006)], optimal design of composite box-beam helicopter rotor blade [S. Suresh (2007)]. However, PSO has the disadvantage of premature convergence to local minimum. So, an improved PSO is proposed to improve its searching capability, which is based on the thought of controlling population diversity. In the process of population evolution, it adaptively adjusts the inertia's weight value and controls nimbly the ability of algorithm's searching over global and local situation. When population diversity reduces to certain extent, population diversity will be improved through mutation operation on part particles of population, such that the population can sustain evolution and improve the probability of searching optimum solution overall situation. Based on the improved PSO algorithm, an optimal scheduling system is developed for rectifier power system in process of zinc electrolysis. The industrial application results show that it can decrease the power consumption and the electric power cost greatly, which brings a huge economic benefit for the enterprise.

The rest of the paper is organized as follows: In Section II an optimal scheduling model aimed to minimize the cost of electrical power and power consumption is presented. Based on the convergence analysis of basic PSO, an adaptive PSO with mutation is proposed to solve such a complicated optimization problem in Section III. Section IV describes an industrial application to an electrolysis process of zinc. Finally, section V concludes the paper.

2. AN OPTIMAL SCHEDULING MODEL

As we know, the power consumption in the process of zinc electrolysis is in a direct ratio to the cell-voltage and in an inverse ratio to the current-efficiency [Guanggui Mei (2001)]. Due to the complexity of the process reaction mechanism, the factors influencing the power consumption are very complicated. The process model based on BP neural network is established for PZE on the basis of mechanism analysis and large number of experiment data in reference [Chunhua Yang (2002)], which describes the relation between the cell-voltage U and the concentration of sulphuric acid (H_2SO_4) Cs(g/l), the concentration of zinc sulphate ($ZnSO_4$) C_{Zn}(g/l) and the current density Dk (A/m^2), and the relation between the current-efficiency η and Cs, C_{Zn} and D_k. The outputs of the two neural networks, i.e. $U_{ij} = U(Dk_i, C_{si}, C_{Zni})$ and $\eta_{ij} = \eta(Dk_i, C_{si}, C_{Zni})$, are the basis of the optimal power scheduling. The structure of the neural network is shown as in Fig. 1.

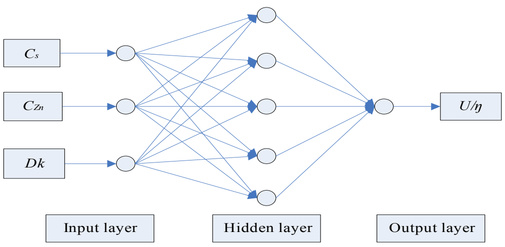

Fig.1 Structure of BP3L-U and BP3L-η

The objective of optimal scheduling for rectifier power system is to decrease the cost of electrical power and power consumption by calculating the optimal current intensity of each series in different pricing period. So, the optimization model is described as Eq. (1).

$$\begin{aligned} \min\ JQ &= \min[k_1(J_1 + J_0) + k_2 Q] \\ &= \min[k_1(\sum_{i=1}^{n} PW_i \times T_i \times P_i + J_0) \\ &\quad + k_2 \sum_{j=1}^{m}\sum_{i=1}^{n} U_{ij} \times Dk_{ij} \times N_j \times B_j \times S_0 \times T_i] \end{aligned} \tag{1a}$$

s.t.

$$\begin{cases} U_{ij} = U(Dk_{ij}, C_{sij}, C_{Znij}) \\ \eta_{ij} = \eta(Dk_{ij}, C_{sij}, C_{Znij}) \\ \sum_{j=1}^{m}\sum_{i=1}^{n} q \times Dk_{ij} \times N_j \times B_j \times S_0 \times \eta_{ij} \times T_i = G_0 \\ Dk_{\min} \le Dk_{ij} \le Dk_{\max}, I_{j,\min} \le I_{ij} \le I_{j,\max} \end{cases} \tag{1b}$$

where n is the number of different price periods in one day, PW_i is the electrical energy consumption (Kwh) in the ith period, T_i is the number of hours (h) in the ith period, P_i is the price (Yuan/Kwh). m is the number of series, U_{ij} is the cell voltage (V), N_j is the number of cells, Dk_{ij} is the current density (A/m^2) of the ith period in J series(A/m^2), B_j is the number of plates in a cell, S_0 is the area of a negative plate(m^2). q is electrochemical equivalent of zinc ($q = 1.2202$ g/A·h), G_0 is the daily planned production of Zn (ton), Dk_{min} and Dk_{max} are the upper and lower limit of current density under the acceptant technical condition of zinc Electrolysis Process respectively, Dk_{min} and Dk_{max} are determined by empirical knowledge of the process. $I_{j,min}$ and $I_{j,max}$ are the upper and lower limit of current in jth series. k_1 and k_2 are the weight coefficients, which are determined by practical requirement of the enterprise.

As shown in Eq. (1), the optimal scheduling problem in rectifier power system of PZE is a typical nonlinear global optimization problem including equality and inequality constraints, along with nondifferentiable neural network process model. It is difficult to be solved by the traditional optimization methods. Hence, PSO is selected in this project as the principle optimization tool to solve such kind of optimization problem.

3 ADAPTIVE PSO WITH MUTUATION

3.1 Basic PSO

In PSO, instead of using genetic operators, each particle (individual) adjusts its "flying" according to its own flying experience and its companions' flying experience. Each particle is treated as a point in a D-dimensional space. The ith particle is represented as $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$. The best previous position (the position giving the best fitness value) of the ith particle is recorded and represented as $P_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of the position change (velocity) for particle i is represented as $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, which is clamped to a maximum velocity specified by the user $V_{\max} = (v_{\max,1}, \cdots, v_{\max,d}, \cdots, v_{\max,D})$. The particles are updated according to Eq. (2).

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_1() * (p_{id} - x_{id}^{t}) + c_2 * r_2() * (p_{gd} - x_{id}^{t}) \tag{2a}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{2b}$$

where c_1 and c_2 are two positive acceleration constants, $r_1()$ and $r_2()$ are random real numbers drawn from [0, 1], t is the iteration times, w is the inertia weight and i is the number of the particle. Eq. (2a) is used to renew particle's velocity according to its previous velocity and the distance of its current position from its own best experience (position) and the group's best experience. Then the particle position is updated according to Eq. (2b). The performance of each particle is evaluated according to a predefined fitness function, which is related to the problem to be solved. The inertia weight w is employed to control the impact of the previous history of velocities on the current velocity, thus to influence the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the “flying points”. A lager value of w facilitates global exploration (searching new areas) while a smaller one tends to facilitate local exploration to fine-tune the current search area.

3.2 Convergence Analysis of basic PSO

The iteration and updating in PSO carries out the strategy that all particles follow the best optimal one in population. If a particle finds a local best position, the other particles quickly fly to it. thus, these particles may trap in local optimum and cannot search in global resolution space again. Thus, the premature convergence phenomena occur.

Experiments demonstrate whether in premature convergence or global convergence in PSO, the population diversity will be severe lack when particles accumulate. The results also illuminate that the severe lack of population diversity will lead to premature convergence.

Here, define parameter $D(t)$ called the population average distance amongst points [KRINK T(2002)] to describe the population diversity. Let L note the diagonal length of search space, M the size of the population, D the dimension of the solution space, x_{id}^{t} the dth dimension coordinate values of the ith particle, $\overline{p}_d$ the average value of the dth dimension coordinate values of all particles. The population average distance amongst points in tth iteration times $D(t)$ is described as following:

$$D(t) = \frac{1}{M \cdot L} \sum_{i=1}^{M} \sqrt{\sum_{d=1}^{D} (x_{id}^{t} - \overline{p}_d)^2} \qquad (3)$$

The population average particle distance describes the distribution discrete degree between the particles in the population. The smaller $D(t)$ is, the more concentrative the population will be.

3.3 Adaptive PSO with Mutation

To avoid the premature convergence, an adaptive PSO with mutation (APSOM) is presented, relying on the strategy of population diversity control to help the optimization method jump out of the local optimum. It will continue to search the solutions in other areas of the solution space when premature convergence occurs. In the process of population evolution, APSOM adaptively adjusts the inertia weight value and controls easily the ability of algorithm’s searching over global solution space and local solution space. When the population diversity reduces to certain extent, i.e., $D(t)$ smaller than a given value, or when there is no obvious change in global optimum value Pgd for a long time, the population diversity will be improved through mutation operation on part particles of population. So, the population can be evolved continuously and improve the capacity of searching global optimal solutions.

(1) Strategy of adaptive inertia weight

The practical searching process of PSO algorithm is non-linear and very complicated. Since the common method of decreasing inertia’s weight linearly and its single style of weight variation, it is limited to adjust for searching ability and is not always adaptive to complicated situation of practical problems. While it is able to change this single adjustment pattern on the inertia’s weight and make it preferably adapt to complicated practical environment.

Define the change rate k of optimal fitness as following

$$k = \left| f(t) - f(t-T) \right| / \left| f(t-T) \right| \qquad (4)$$

Where, $f(t)$ is optimal fitness of generation t of population; $f(t-T)$ is optimal fitness of generation $t-T$ of population, k is relative change rate of optimal fitness on the recent evolution generation T of population. The value of inertia weight w is adjusted adaptively with the value of k, as shown in Eq. (5),

$$w = \begin{cases} \alpha_1 + r/2, & k \geq 0.05 \\ \alpha_2 + r/2, & k < 0.05 \end{cases} \qquad (5)$$

Where, r is a uniformly distributed random number in the interval [0, 1]. When $k \geq 0.05$, namely that optimum adaptive value of population change is the biggest in the process of evolution and the population is in the exploring stage, taking bigger value of inertia weight benefits to the algorithm convergence, its mathematics expected value is $E(w)=\alpha_1+0.25$. When $k < 0.05$, namely that optimum adaptive value of population change is minor in the evolving process and population is in the developing stage, taking minor value of inertia weight is beneficial to obtaining the accurate solution. $E(w)= \alpha_2 + 0.25$ and $\alpha_1 > \alpha_2$. Generally, α_1 and α_2 are taken respectively 0.6 and 0.2.

(2) Mutation Operation

Population diversity loses continually in the PSO algorithm, with searching iteration in progress, which may lead to premature convergence. Therefore, when population evolves to certain extent, mutation operation is carried out to improve population diversity. These particles carrying out the mutation operation will enter other search areas. In the later evolution process the algorithm will find the new optimal solutions. Repeat the searching procedure, the algorithm can search the global optimal solutions.

When $D(t)$ is smaller than certain given value, or when there is no obvious change in global optimum value Pg for a long time (for example, iterated over 10 times), mutation operation is executed according to certain probability p_m for part particles in population. And p_m is taken as random value on interval [0.1, 0.3]. Specific procedure as follows: Firstly sort for all particles in population according to the size of corresponding adaptive value. Then select out m particles with best adaptive value and produce correspondingly m random values r_i (i = 1, 2, ..., m) in interval [0, 1]. If $r_i < p_m$, produce new position of corresponding particle according to

Eq. (6). At the same time, record the searched optimal position of this particle up to now and begin a new iteration.

$$x_{id}^{t+1} = x_{id}^{t} * (1 + 0.5 * \eta) \tag{6}$$

Where, η is randomly drawn from Gauss(0, 1) function.

3.4 Performance analysis

The algorithm performance is tested through optimization of three typical functions and comparison with basic PSO. Rosenbrock function $f_1(x)$ is an ill-conditioned single peak quadratic function and is difficult to minimize. Rastrigin function $f_2(x)$ and Griewank function $f_3(x)$ are multi-modality functions.

1) Rosenbrock function

$$f_1(x) = \sum_{i=1}^{n} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2), \tag{7}$$
$$-30 \le x_i \le 30$$

Whose optimal state and the optimal value are

$$\min f(x*) = f(1,1,\ldots 1) = 0.$$

2) Rastrigin function

$$f_2(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10), \tag{8}$$
$$-5.12 \le x_i \le 5.12$$

Whose optimal state and the optimal value are

$$\min f(x*) = f(0,0,\ldots 0) = 0.$$

3) Griewank function

$$f_3(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left|\frac{x_i}{\sqrt{i}}\right| + 1, \tag{9}$$
$$-600 \le x_i \le 600$$

Whose optimal state and the optimal value are

$$\min f(x*) = f(0,0,\ldots 0) = 0$$

The evaluation index to Evaluate different optimization algorithm is given as follows:

①the average most optimal fitness value F_{ave}: mathematical average value of optimal function value in M times experiments.

②average success ratio R_{as}

$$R_{as} = Ms / M \tag{10}$$

where M is the total times of experiments and Ms is the successful times.

③ average generations T_{ave}

$$T_{ave} = \sum_{n=1}^{Ms} T_n^s / Ms \tag{11}$$

where T_n^s is the number of the generations in the nth successful optimization.

In these experiments, the dimension is 30, the maximal times of iteration is 5000, population size is 50 and the maximal velocity is the range value of the test function. Set w from 0.9 to 0.4 in basic PSO. Let c_1=c_2=2.0, D_{min}=0.001. Each optimization experiment is repeated for 50 times to eliminate the influence of the accidental factors. The results are listed in Tab. 1.

Tab.1 Comparison of simulation results

	APSOwM		Basic PSO	
	F_{ave}	R_{as}	F_{ave}	R_{as}
$f_1(x)$	7.3144	38/50	43.0793	35/50
$f_2(x)$	1.324×10^{-9}	48/50	35.3475	3/50
$f_3(x)$	7.262×10^{-11}	43/50	2.851×10^{-9}	40/50

From Tab.1, it is shown that APSOM is superior to basic PSO in all test experiments of the three test functions. To function $f_1(x)$, the optimization result of APSOM has a difference to the global minimum of the function itself, but the result is superior to basic PSO. In the experiments of function $f_2(x)$, the optimization results are improved obviously and all experiments find the global minimum, while it is difficult for basic PSO to converge to the global minimum. However, the performance improvement in function $f_3(x)$ optimization is less compared with the basic PSO due to its function characteristic trends to a single peak function when the space dimension is over 10, which weaken its adaptive advantage.

In order to clearly analyze the optimization mechanisms of APSOM and basic PSO, the changes of the population average distance amongst points $D(t)$ along with the optimization generations (1000 times) in a optimization of function $f_2(x)$ are listed in Fig. 2 and Fig. 3.

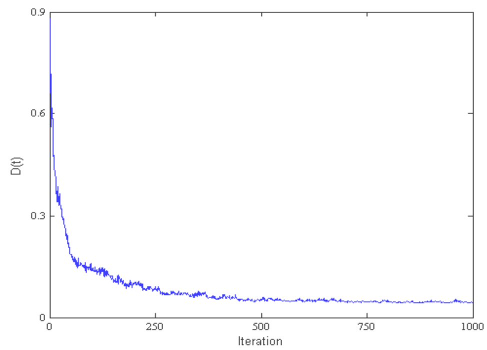

Fig.2 Diversity curve of basic PSO

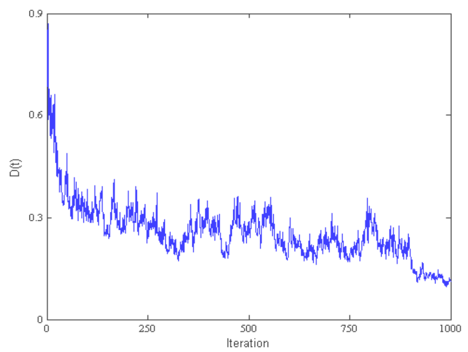

Fig.3 Diversity curve of APSOM

From Fig.2 and Fig.3, we can find that the linearly decreasing weight of the basic PSO can increase the search ability slowly and *D(t)* approximately decreases along with the increasing of the generation leading to fast loss of the population diversity and easily trapping into local minimum. On the contrary to APSOM, the adaptive weight adjustments improve the flexibility of the search capacity in local search and global search capacity that enhances the search efficiency in total search process and increases the population diversity. Moreover, by using the mutation strategy, it prevents the fast loss of the population diversity, improves the global search capacity, and easily jumps out the local minimum.

4 AN INDUSTRIAL APPLICATION

4.1 Pre-treatment

In the optimization model as Eq.(1), there exist some constraints in Eq. (1b). Therefore, penalty function method is used to turn an optimizing problem with constraints to an optimizing problem without constraints through combining the constraints into the objective function. In accordance with Eq.(1), a new objective function is constructed as Eq.(12).

$$JQ' = JQ\left(Dk_{ij}\right) + \sigma \times \left(G - G_0\right)^2 \tag{12}$$

Where σ is the penalty factor, which selects a large enough value during optimization. Here, it is selected as 1000 through trial and error method.

To ensure the optimization in a feasible constraint domain, the boundaries of Dk_{ij} are modified as Eq. (13).

$$Dk_{ij} = \begin{cases} Dk_{j\max} - \left(Dk_{ij} - Dk_{j\max}\right) \bmod \left(Dk_{j\max} - Dk_{j\min}\right) \\ \qquad if \quad Dk_{ij} > Dk_{j\max}; \\ Dk_{ij} \qquad if \quad Dk_{j\min} \le Dk_{ij} \le Dk_{j\max}; \\ Dk_{j\min} + \left(Dk_{j\min} - Dk_{ij}\right) \bmod \left(Dk_{j\max} - Dk_{j\min}\right) \\ \qquad if \quad Dk_{ij} < Dk_{j\min}. \end{cases} \tag{13a}$$

$$Dk_{j\max} = \begin{cases} Dk_{\max}, & if \quad I_{ij} \ge Dk_{\max} \times B_j \times S_0 \\ I_{j\max} / (B_j \times S_0), & else \end{cases}$$
$$Dk_{j\min} = \begin{cases} Dk_{\min}, & if \quad I_{ij} \le Dk_{\min} \times B_j \times S_0 \\ I_{j\max} / (B_j \times S_0), & else \end{cases} \tag{13b}$$

Thus, Dk_{ij} satisfies the boundaries constraints all the time.

The stop criterion in optimization process is that relative error is less than 0.2% between planned product output and calculated product output, and the relative error of fitness value is less than 0.05%, otherwise t achieves a predefined maximum generation t_{max}.

4.2 Application results

In a large-scale zinc smeltery there are two subsystems, where there are four rectifier series in subsystem 1, and there are three rectifier series in subsystem 2. It consumes electrical energy more than 100 million KWh a year. It is significant to decrease the electrical energy cost in the electrolysis process of zinc and balance the power grid load.

There are four varying pricing periods, the price is describes as $p_i = c_i \times A$, where c_i is the pricing coefficient in the *i*-th period, A is the basic price, 0.392 yuan/KWh. Here, the hours of each period t_i ranges from t_1 to t_4 and has its own values of (3, 7, 6, 8), c_i ranges from c_1 to c_4 and has its own values of (1.9, 1.35, 1.0, 0.4). Set m=7, N_1~N_7=(240, 240, 246, 192, 208, 208, 208), B_1~B_7=(34, 34, 46, 54, 56, 56, 57), S_0 = 1.13 m^2, $Dk_{\min}$= 200 A/m^2, $Dk_{\max}$=650 A/m^2, k_1=0.95, k_2=0.05, the daily planned product output G_0=960 ton.

The scheme of optimal scheduling rectifier power system based on the proposed optimization algorithm is listed in Tab.2.

Tab.2 Scheme of optimal scheduling rectifier power

	Current intensity /*A*			
series	flat period	peak period	high period	valley period
I	18364.76	7684.00	7991.36	22821.48
II	19248.42	7684.00	7991.36	23858.82
III	24430.60	10396.00	11123.72	32851.36
IV	27764.10	12204.00	13302.36	36856.08
V	28792.40	12656.00	14174.72	39676.56
VI	28792.40	12656.00	14174.72	39676.56
VII	29306.55	12882.00	12882.00	39676.56

According to this optimal scheme to schedule power supply for electrolysis production, the practical running results are shown as follows.

The practical output is 959 ton and the relative error satisfies the expected value; the daily total cost of electrical power is 0.9865 million *yuan* (RMB), power consumption is 2.8798*10^6 KWh and the average power consumption per ton of zinc is 3002.4 KWh. While before this scheme is used, average power consumption per ton of zinc is 3583.4 KWh/ton. Obviously, with the scheme of optimal scheduling of rectifier power, the cost of electrical power is decreases by 14.3% and the average power consumption is reduced by 16.3%. It is concluded that this optimal scheduling scheme of rectifier power system contributes to decreasing the cost of electrical power and power consumption greatly under the condition of ensuring the product output and quality. Moreover, from Tab.2, it is shown that the current intensity in valley period is over three times as that in the peak period, which balances the load of power grid and benefits the safety and stability of power grid.

The optimal scheduling system for rectifier power system has been put into use since Jan. 2006. The electrolysis process of zinc has been running steadily, economically and safely. The practical running results demonstrate that the running of the optimal scheduling system can greatly decrease the power consumption and the electric power cost, and bring huge economic benefits for the enterprise.

5 CONCLUSIONS

In this paper, the optimal scheduling problem for rectifier power system is described and the optimal scheduling model is presented. Considering the complexity existed in the model, an improved PSO is proposed to deal with the optimization problem. The scheme of optimal scheduling rectifier power system is put into use and satisfactory effect has been obtained. The main work is summarized as follows:

(1) An optimal scheduling model to lower the power consumption and electric power cost is presented. It is a typical nonlinear global optimization problem with equality and inequality constraints, including nondifferentiable neural network process model.

(2) An adaptive PSO with mutation is proposed aimed to the model complexity. It improves the performance and enhances the global searching capacity by introducing the strategy of adaptive adjustment of inertia weight and mutation operation on part particles of population.

(3) The optimal scheduling system for rectifier power system based on the proposed optimization algorithm is developed and is put into use in a large-scale hydrometallurgical smeltery. The running results show that the power consumption and the electric power cost in zinc electrolytic process is decreased obviously, which brings great economic benefits for the enterprise. Moreover, it can balance the power grid load efficiently.

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