Application of Multi-objective Particle Swarm Optimization in Condenser Control System Parameters Tuning

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Abstract: The control system of condenser includes three mutually coupled subsystems: PID control system of water level, pressure, and condensate sub-cooling degree. For the situation of complex coupling among systems during PID parameter tuning, a multi-objective particle swarm optimization (MOPSO) based on Pareto optimality is applied. This method provides a way to tune PID parameters of every coupled control system without decoupling, which can avoid uncertainty and influence of coupling. This method takes dynamic performances as the optimization objectives, and selects MOPSO to obtain Pareto-optimal solution set. The MOPSO combines particle swarm optimization (PSO) with Pareto dominance relationship for a multi-objective optimization. The algorithm of MOPSO adopts a comprehensive learning mechanism to update optimal set, which improves precision and diversity of the solutions [1]. The simulation result proves that the MOPSO can tune PID parameters of coupled control systems better than classical engineering tuning method.

Keyword: Condenser control system, MOPSO, PID parameter tuning.

1 Introduction

As the most important cold source in secondary loop, condenser plays an irreplaceable role in the fluid circulation and the energy conversion [2]. In order to ensure the condenser works securely and reliably, there are 3 major variables that should be in control: water-level, pressure, and condensate sub-cooling degree. The water level needs to be controlled in a relatively stable range, which can prevent circulating cooling water pipe from being flooded by high water level, or condensate pump from dissipation of cavitations by low water level; The pressure needs to be controlled at a relatively low constant, which can provide a low and steady back pressure for the turbine and ensure its thermal efficiency and stability; condensate sub-cooling degree is the difference between the saturation temperature and the actual temperature, it needs to be controlled in a range close to 0℃, which can avoid the damage of oxygen to the secondary loop device.

It can be seen that as a multi-input multi-output (MIMO) device, the control system of condenser consists of three control systems: water-level, pressure, and condensate sub-cooling degree control system. The three control systems have separate measuring devices, PID controllers, and actuators. Also the three control systems are interconnected and coupled because of a common control object--condenser. For example, condensate temperature and sub-cooling degree will change when adjusting the water level of the condenser by the way of water replenishing. As another example, saturation temperature and condensate sub-cooling degree will change when regulating the pressure by adjusting the circulating cooling water flow. Therefore, the three control systems are mutually coupled.

For control parameters tuning of the coupled control systems, the traditional method is to tune each control system one by one. When tuning the parameters of the A control system, we need to estimate a complete set of parameter values (not final setting values) for other control systems, then tune parameters of A control system based on these estimated parameters. Take this as an example, other control systems are tuned one by one. The traditional method has a limitation in the parameter tuning of the coupled control systems. The limitation is that the estimated parameter values may not be accurate certainly, and the final parameter setting values will be inaccurate based on inaccurate estimated parameter values. In addition, the more the number of coupled control systems is and the stronger the coupling property is, the sharper the limitation will be. The main reason for this limitation is that traditional method cannot tune parameters of multiple control systems simultaneously, but needs decoupling parameters estimation. In this paper, a multi-objective particle swarm optimization (MOPSO) algorithm is used to tune control parameters of multiple control systems simultaneously without decoupling, so as to overcome the limitation of traditional method.

2 Design of multi-objective particle swarm optimization algorithm based on Pareto optimization

2.1 Multi-objective optimization problem and Pareto dominance relationship[3]

The multi-objective optimization problem (MOP), which is generally accepted in the field of optimization, is defined as follows:

There is a multi-objective optimization problem

$$\begin{aligned} \max\ & f(x) = [f_1(x), f_2(x), ..., f_n(x)]^T \\ s.t.\ & g_i(x) \le 0 \qquad i = 1, 2, ..., j \\ & h_i(x) = 0 \qquad i = j+1, ..., p \end{aligned}$$

In the above definition, $x = (x_1, x_2, ..., x_n)^T$ is a n-dimensional vector of space R^n, space R^n is the decision space of the MOP, $f_i(x)(i = 1, 2, ..., n)$ is a sub objective function of the MOP, the space which the n-dimensional vector $[f_1(x), f_2(x), ..., f_n(x)]^T$ lies in is the target space of the MOP, $g_i(x) \le 0(i = 1, 2, ..., j)$ and $h_i(x) = 0(i = j+1, ..., p)$ are inequality and equality constraints.

The central purpose of MOP is that in most cases each objective is conflicting, an improvement in one objective function may lead to deterioration of other objective functions, and it is almost impossible to achieve multiple objectives at the same time. The only way is to coordinate and compromise all the objective functions. Its optimal solution is no longer an optimal solution for all objectives, but Pareto optimal solution. Usually, the number of Pareto optimal solutions is multiple, and the optimal solution set of the MOP contains all the Pareto optimal solutions. Facing to practical instance, we need to select some of the Pareto optimal solutions according to the subjective demand.

The relevant definitions of Pareto optimality are as follows:

1) Pareto dominance relationship: feasible solution x^0 dominates x^1, record as $x^0 \succ x^1$, if and only if

$$f_i(x^0) \ge f_i(x^1), \quad i = 1, 2, ..., M$$
$$f_i(x^0) > f_i(x^1), \quad \exists i \in \{1, 2, ..., M\}$$

2) Pareto optimal solution: if feasible solution x^0 is Pareto optimal solution, if and only if

$$\neg \exists x^1 : x^1 \succ x^0$$

3) Pareto optimal solution set: a set of all Pareto optimal solutions

$$P_S = \{x^0 \mid \neg \exists x^1 \succ x^0\}$$

4) Pareto optimum front-end: the area in which all the optimal objective function values are formed

$$P_F = \{f(x) = (f_1(x), f_2(x), ..., f_M(x)) \mid x \in P_S\}$$

Take the two objective optimization problem as an example, Fig.1 depicts the distribution of the dominated and the non-dominated solutions in the objective space. In Fig.1, f1 and f2 are two objective functions for maximization.

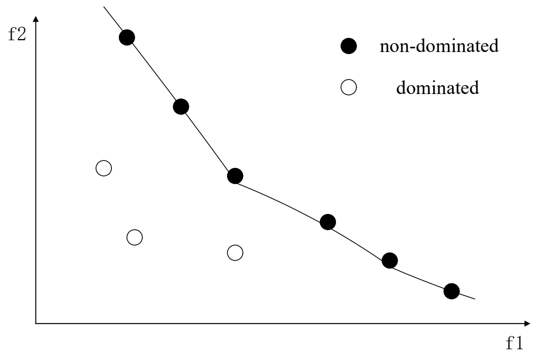

Fig.1 Distribution of the dominated solutions and the non-dominated.

2.2 Multi-objective particle swarm optimization algorithm based on Pareto optimization

Particle swarm optimization algorithm (PSO) is an evolutionary algorithm based on swarm intelligence which was put forward by Kennedy and Eberhart who were inspired by avian swarm intelligence in 1995. In PSO, each particle represents a candidate solution of the solution space, particles travel at a certain speed in search space, the speed of particles is adjusted dynamically according to the travel experience, thus the global search of the whole space is realized.

Multi-objective particle swarm optimization algorithm (MOPSO) adds the external elite set on the basis of particle swarm algorithm. In addition to the updating of the particle itself, we also need to update the external elite set based on the Pareto dominance relationship after one iteration. When all the iterations are completed, the external elite set is the Pareto optimal solution set of the optimization problem. The key steps of MOPSO contain the update of own best position, selection of global best position, and the update of external elite set.

2.1.1 Update of own best position

After one iteration, if the particle's own best position dominates the current position, then the own best position remains unchanged; if the particle's own best position is dominated by the current position, then update the own best position to the current position; If the two do not dominate each other, generate a random number **s** of [0,1], if **s** <0.5, then update the own best position to the current position, otherwise the own best position remains unchanged.

2.1.2 Selection of global best position

The global optimum position of MOPSO is not a deterministic solution, but a non-dominated solution that is randomly selected from the optimal solution set after iteration.

2.1.3 Update of external elite set

The external elite set is used to preserve the non-dominated solutions arising in iterations. After one iteration, if the current particle is dominated by any member of the elite set, then the current particle is not allowed to join the elite set; if the current particle dominates some members of the elite set, remove the members that are dominated and add the current particle to the elite set; if the current particle and all elite set members do not dominate each other, add the current particle to the elite set.

2.1.4 Basic steps of algorithm

The steps of this algorithm:

Step1. Set the maximum number of iterations to **zmax**, set the initial iteration step to **z=0**, set external elite set. The initial positions and velocities of the particle swarm are generated randomly in the search range, obtain the initial objective function values according to the initial position, and obtain the initial elite set members according to the Pareto dominance relationship. Set the initial position for each particle's own best position;

Step2. Select the best global position from the elite set;

Step3. Use the iterative formula of particle swarm algorithm to update the velocity and position of particles;

Step4. Ensure the velocity and position of particles within specified limits: if the velocity of a particle in one or more dimensions is beyond the specified range, randomly select a velocity within the specified range as the velocity of the particle in that dimension; if the particles travel beyond the specified range, randomly select a position within the specified range as the current position of the particle in that dimension;

Step5. Update own best positions of particles;

Step6. Update external elite sets;

Step7. Verify if the termination condition is met. If the answer is yes, stop the algorithm search, output the external elite set as the final result; if the answer is no, go to Step2.

3 Application of MOPSO in tuning control parameters of condensers

3.1 Model of condenser and its control system

Establish the simulation model of condenser by S-fun module in Matlab/Simulink. The inputs of the condenser model are flow and specific enthalpy of turbine exhaust, flow of condenser condensate, flow and temperature of replenishing/drainage water, flow and temperature of circulating cooling water, flow and specific enthalpy of heating exhaust steam; the outputs are water-level, pressure, and condensate sub-cooling degree. Establish the control systems model in the same simulation platform. Among the three control systems, the water level control system reduces the deviation between the actual water level and the setting water level by adjusting the flow of replenishing/drainage water; the pressure control system reduces the deviation between the actual pressure and the setting pressure by adjusting the circulating cooling water flow; condensate sub-cooling degree control system regulates the condensate temperature by regulating the flow of heating exhaust steam, and controls condensate sub-cooling degree close to 0℃. The model is shown in Fig.2.

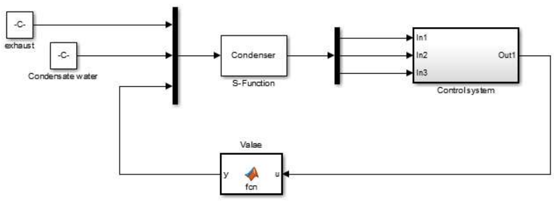

Fig.2 The model of condenser control system

3.2 Optimization model of this subject

In order to meet the requirements of stability, robustness and rapidity, and to optimize as much as possible, we select step response performance indexes of three control systems as objective functions or constraint conditions, parameters of the three controllers as the optimized objects. This optimization model is:

$$\begin{aligned} \min \quad & f(kp1, ki1, kp2, ki2, kp3, ki3) = [e_{ss}, \sigma_{\max}, t_s]^T \\ s.t. \quad & \sigma_{\max} 3 \le 0.1m \\ & t_s 3 \le 200s \\ & kp_{\min} \le kp \le kp_{\max} \\ & ki_{\min} \le ki \le ki_{\max} \end{aligned}$$

In the above definition, $kp1$, $ki1$, $kp2$, $ki2$, $kp3$, $ki3$ are control parameters of three PID controllers; $e_{ss} = (e_{ss}1, e_{ss}2)^T$ are the steady state errors of pressure and condensate sub-cooling degree; $\sigma_{\max} = (\sigma_{\max}1, \sigma_{\max}2)^T$ are the maximum disturbance responses of pressure and condensate sub-cooling degree; $t_s = (t_s1, t_s2)^T$ is the adjusting time of pressure and condensate sub-cooling degree; $\sigma_{\max}3$ is the maximum disturbance response of water level; t_s3 is the adjusting time of water level; $kp_{\max} = (kp_{\max}1, kp_{\max}2, kp_{\max}3)^T$, $kp_{\min} = (kp_{\min}1, kp_{\min}2, kp_{\min}3)^T$, $ki_{\max} = (ki_{\max}1, ki_{\max}2, ki_{\max}3)^T$, and $ki_{\min} = (ki_{\min}1, ki_{\min}2, ki_{\min}3)^T$ are the search scope of control parameters.

The reason why setting the performance indexes of water level as constraint conditions rather than objective functions is that the water level does not need to be precisely controlled. It only needs to be controlled within a certain range.

3.3 Determination of search scope

The search scope is a rough scope that contains Pareto optimum solutions. MOPSO does not require very high precision in the search scope. In this paper we adopted a trial and error method based on the ISTE performance index to get the search scope. The method is based on two criteria: First, make sure all the solutions of control parameters in this scope are feasible solutions; second, while trying to figure out the scope, if the ISTE performance index changes slowly, then the kp and ki values in the scope should be as small as possible, so as to improve the stability of the control system.

The ISTE performance index is represented by $\int t \cdot [e(t)]^2 dt$.

With the changes of control parameters, changes of ISTE performance indexes are shown in Fig.3.

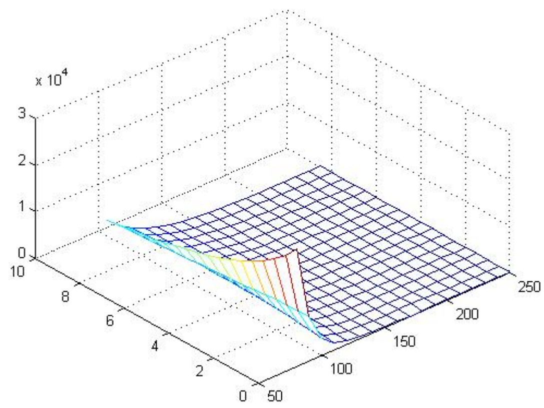

Fig.3.1 Changes of ISTE performance indexes (pressure control system)

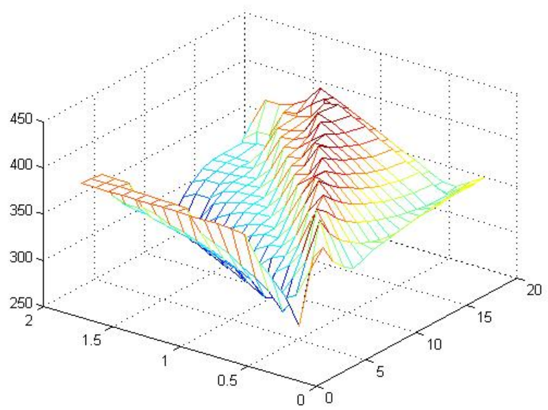

Fig.3.2 Changes of ISTE performance indexes (condensate sub-cooling degree control system)

According to the two criteria and Fig.3, the search scope of control parameters is determined as follows:

$kp_{max} = (20, 200, 5)$;
$kp_{min} = (1, 50, 0.1)$;
$ki_{max} = (1, 8, 1)$;
$ki_{min} = (0, 0, 0)$.

3.4 Application of multi-objective particle swarm optimization

For general optimization problems, the values of the objective functions are obtained by calculation; for control parameter optimization problems, the values of the objective functions are obtained by simulation. Bring a set of feasible control parameters into the simulation model and obtain the performance indexes as the values of the objective functions after running. The application process of MOPSO in control system parameter tuning is shown in Fig.4.

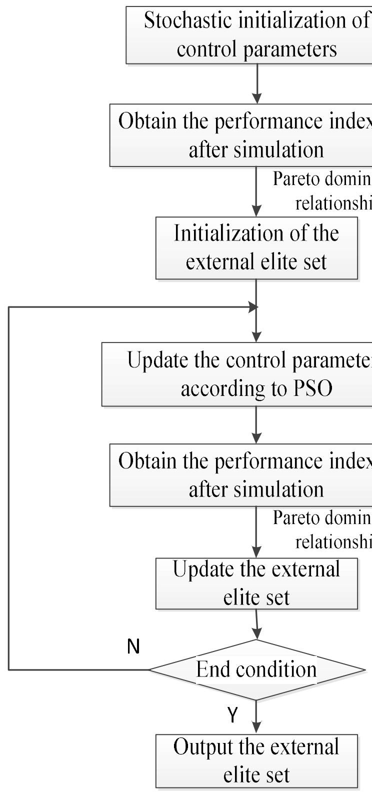

Fig.4 The application process of MOPSO

4 Simulation and verification of search results

We obtained 70 Pareto optimal solutions after search. Choose some representative solutions and represent their corresponding objective function (performance index) values as shown in Table 1 and Table 2.

Table 1 Representative solutions

Solution No.	kp1	ki1	kp2	ki2	kp3	ki3
1	10.82	0.71	53.68	4.67	9.44	0.45
2	16.53	0.64	195.7	4.20	4.60	0.34
3	10.15	0.47	54.95	4.98	8.54	0.31
4	7.01	0.09	198.0	4.80	9.55	0.62
5	11.78	0.65	113.7	4.04	5.27	0.02

Table 2 Objective function values

Solution No.	$e_{ss}1$	$\sigma_{max}1$	t_s1	$e_{ss}2$	$\sigma_{max}2$	t_s2
1	0.00	1.71	120.7	0	2.3	140.5
2	0.07	0.86	179.3	0	1.3	136.3
3	0.01	1.69	116.7	0	2.3	171.6
4	0.05	0.88	163.4	0	1.2	127.5
5	0.04	1.23	157.9	0	1.7	81.7

When the amount of steam to the condenser step falls from 100% to 90%, the step responses corresponding to the control parameters in each group are shown in Fig.5.

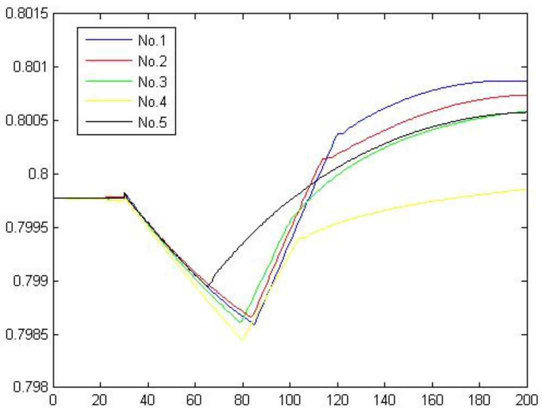

Fig.5.1 Step responses of water-level

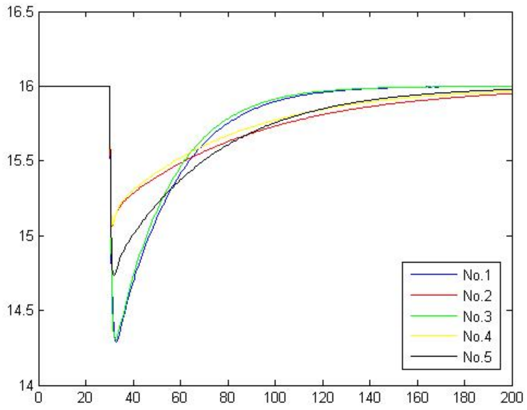

Fig.5.2 Step responses of pressure

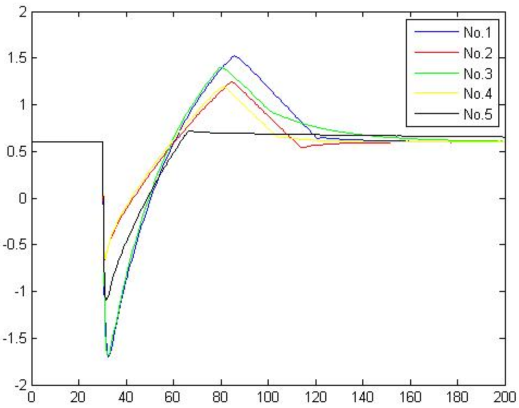

Fig.5.3 Step responses of condensate sub-cooling degree

We can see through table 2 and Fig.4 that Pareto optimal solutions have the features of diversity: solution No.1 focuses on the optimization of ess1; solution No.2 focuses on the optimization of $\sigma_{max}1$; solution No.3 focuses on the optimization of t_s1; solution No.4 focuses on the optimization of $\sigma_{max}2$; solution No.5 focuses on the optimization of t_s2. Although each Pareto optimal solution is different from each other, they are equal in status because of non-domination with each other. The decision maker will choose one or several of them that conform to the actual situations.

In order to verify the effect of MOPSO in parameters tuning of coupled control systems, we compare the tuning result with the result of traditional method. The traditional method adopts empirical formulas based on ISTE criterion[4] and tunes each control system one by one after decoupling. The proposed method chooses the equilibrium Pareto optimal solution No.5 as the tuning results.

When the amount of steam to the condenser step falls from 100% to 90%, the step responses of MOPSO method and traditional method are shown in Fig.6.

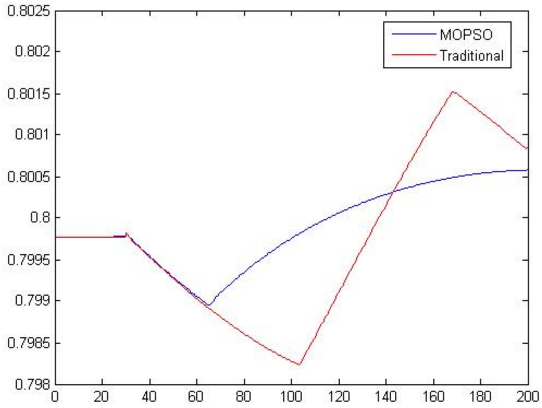

Fig.6.1 Step responses of water-level

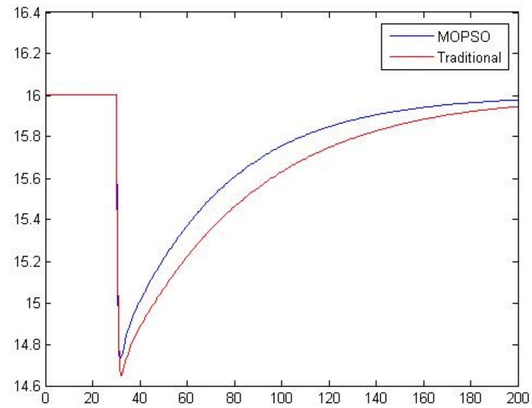

Fig.6.2 Step responses of pressure

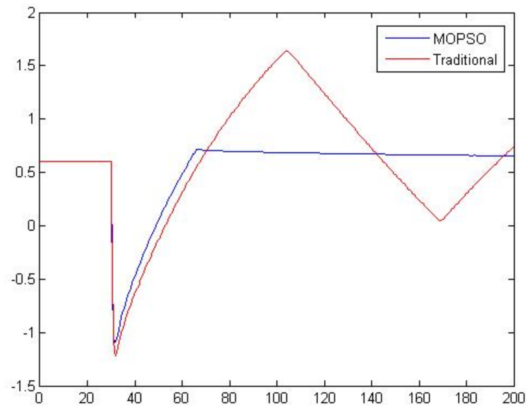

Fig.6.3 Step responses of sub-cooling degree

When the steam turbine load rises rapidly, responses of MOPSO method and traditional method are shown in Fig.7.

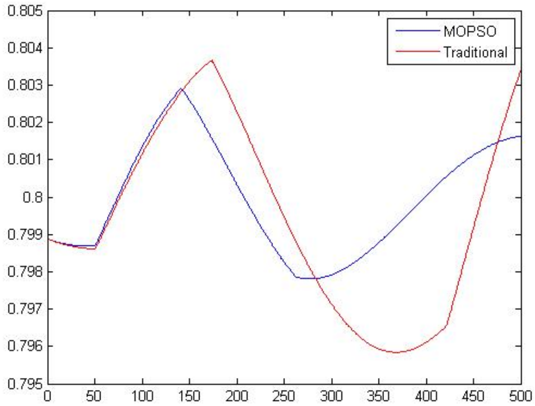

Fig.7.1 Load rise responses of water-level

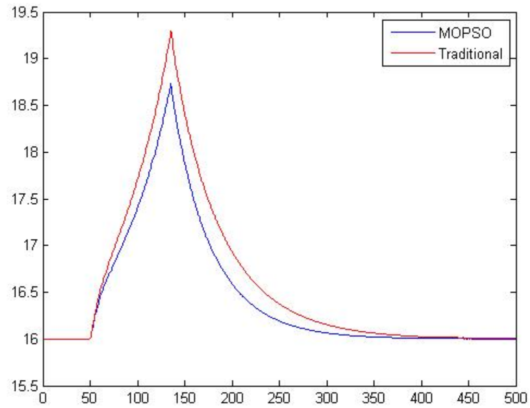

Fig.7.2 Load rise responses of pressure

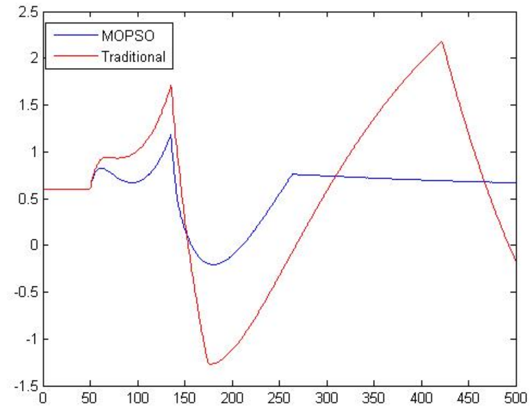

Fig.7.3 Load rise responses of sub-cooling degree

5 Conclusions

In this paper, a MOPSO based on Pareto dominance relation is proposed for parameters tuning of condenser control system. Simulation results show that this method can optimize all performance indexes of a coupled control system at the same time without decoupling. After one operation, MOPSO can obtain a number of Pareto optimal solutions with different emphases. Decision makers can take their own choice in accordance with actual requirements. From this point of view, MOPSO achieves the relative optimization of different indexes. Comparing this method with the traditional tuning method, this method obtained better result. And the Pareto optimal solution set has the feature of diversity and is flexible in solving specific problems. Moreover, the method is general in this paper. It can be extended to a wider range, even the whole system.

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