Control particle swarm optimization for unit commitment problem under emissions reduction

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Abstract

The control particle swarm optimization (CPSO) algorithm is introduced to solve the unit commitment problem under the background of emissions reduction. Because the standard particle swarm optimization algorithm is easy to fall into local optimal solution. The closed loop control concept and feedback mechanism of classical control theory are posited, each particle is considered as controlled object to meet the changing needs in searching process, while dynamically adjust the inertia weight by proportion-Integra-derivative (PID) controllers according to the adaptation value of each step. These strategies greatly ensure the diversity of particles and improve the global search ability of the algorithm. The simulation results show that CPSO algorithm can reduce the dimension of the problem and ensure the feasibility of the particle in the optimization process, while it also has good convergence characteristics and global search ability.

Keywords: power system, emissions reduction, unit commitment, control particle swarm optimization

1 Introduction

From the view of mathematical, the unit combination problem is a multi-constraint non-deterministic polynomial (NP) hard combinatorial optimization problem (K. H. Abdul-Rahman et al.) [1]. It is difficult to obtain theoretically optimal solution. The typical algorithms for solving model include heuristics approach (S.K. Tong et al.) [2], dynamic programming (C.K. Pang) [3], branch and bound method (G.S. Lauer) [4], Lagrangian relaxation method (S.Dekrajangpetch et al., C.P. Cheng et al., W. Ongsakul et al.) [5-7] and the modern intelligent algorithm (S.S. Li et al., Z. Li et al., J.L. Lu, X.H. Zhang et al.) [8-11]. However, these algorithms have one or another defect (K. Han et al.) [12]. If the environmental constraints are considered into the model, the problem will become more complexities. But it is important to economic operation of power systems through improving the accuracy and speed of solution under various constraints. In this context, an objective function of emission reduction unit commitment is posed which considering the minimum cost and minimum emission targets together by introducing emission price factor, and then, the original multi-objective problem can be transferred into a single objective problem, while a variety of constraints can be easily considered, in order to obtain the reasonable compromise between energy consumption and emissions.

In the specific solving algorithm, this paper presents a new set of inertia restructuring strategy through introducing the concepts of feedback mechanisms and closed-loop control system of control theory into the PSO system, then a control particle swarm optimization (CPSO) algorithm is formed. In this algorithm, a closed-loop control system is constructed while each particle sets as a controlled objective. Fitness value of particle is used as the output variable and feed backed to closed-loop in the iterative process, and the updated inertia weight is calculated through a designed PID controller which has been widely used in industrial due to its single structural and robustness, then the velocity and position of the particle is adjusted. CPSO algorithm can satisfy the needs of each particle and greatly ensure the diversity of the population of particles, while improving the search capabilities of PSO algorithm.

2 Mathematic models

The goal of unit commitment optimization is to optimize the status and contributions of generators in the calculation scheduling cycle, while satisfying the some constraints, in order to achieve minimum energy cost or minimum pollutant emissions.

2.1 OBJECTIVE FUNCTION

2.1.1 Minimum Energy Cost

The objective function can be expressed as follows:

$$\min F\left(\eta, P^{gen}\right)=\sum_{t=1}^{T}\sum_{i=1}^{N}\left\{f_i\left(P_{i,t}^{gen}\right)\eta_{i,t}+S_{i,t}^{up}+S_{i,t}^{down}\right\}, \quad (1)$$

$$f_i\left(P_{i,t}^{gen}\right)=\rho_i+\mu_i P_{i,t}^{gen}+\varphi_i\left(P_{i,t}^{gen}\right)^2, \quad (2)$$

$$S_{i,t}^{up}=S_i^{up}\eta_{i,t}\left(1-\eta_{i,t-1}\right), \quad (3)$$

$$S_{i,t}^{down}=S_i^{down}\eta_{i,t-1}1\left(-\eta_{i,t}\right), \quad (4)$$

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i is index for the number of units, i=1,2, …, N, N is the total number of units; t is index for time, t=1,2, …, T, T is the total number of periods in the scheduling period. $\eta_{i,t}$ is the start-up and shut-down statue of unit i at time t. The start-up of unit is 1 and shut-down of unit is to 0. $S_{i,t}^{up}$ is the cost of start-up -and $S_{i,t}^{down}$ is the cost of shut-down for unit i at time t respectively. S_i^{up} is the constant coefficient of cost of start-up and S_i^{down} is the constant coefficient of cost of shut-down for unit i at time t respectively. $f_i(P_{i,t}^{gen})$ is the generation costs of unit i, in \$, ρ_i, μ_i and φ_i are cost coefficients of unit i. $P_{i,t}^{gen}$ is the generation level of unit of unit i at time t, in MW.

2.1.2 Minimum Pollutant Emissions

The objective function can be expressed as follows:

$$\min E\left(\eta, P^{gen}\right)=\sum_{t=1}^{T}\sum_{i=1}^{N}\left\{e_i\left(P_{i,t}^{gen}\right)\eta_{i,t}+S_{i,t}^{up}+S_{i,t}^{down}\right\}, \qquad (5)$$

$$e_i P_{i,t}^{gen}=\alpha_i+\beta_i P_{i,t}^{gen}+\gamma_i\left(P_{i,t}^{gen}\right)^2, \qquad (6)$$

$e_i(P_{i,t}^{gen})$ is the emission costs of unit i. α_i, β_i and γ_i are cost coefficients of unit i, in \$. The other symbols are same as those in last section.

2.1.3 Total Objective Function

Considering the minimum energy cost and minimum pollutant emissions together by introducing an emissions price factor $\theta_{i,t}$, the multi-objective problem turned into a single objective problem and the total objective function is defined mathematically as follows:

$$\min F^{total}\left(\eta, P^{gen}\right)=\sum_{t=1}^{T}\sum_{i=1}^{N}\left\{\left[f_i\left(P_{i,t}^{gen}\right)+\theta_{i,t}e_i\left(P_{i,t}^{gen}\right)\right]\eta_{i,t}+ S_{i,t}^{up}+S_i^{down}\right\}, \qquad (7)$$

The emissions price factor $\theta_{i,t}$ is defined as the proportion between maximum energy cost and maximum pollution emission of unit i, $P^{gen}_{i,max}$ is the maximum generation capacity of unit i:

$$\theta_{i,t}=f_i\left(P_{i,\max}^{gen}\right)/e_i\left(P_{i,\max}^{gen}\right), \qquad (8)$$

2.2 CONSTRAINTS CONDITION

Power balance constraints:

$$\sum_{i=1}^{N}P_{i,t}^{gen}\eta_{i,t}-L_t=0. \qquad (9)$$

Spinning reserve constraints:

$$\sum_{i=1}^{N}P_{i,\max}^{gen}\eta_{i,t}\geq L_t+R_t, \qquad (10)$$

Up and down generation constraints of unit:

$$P_{i,\min}^{gen}\leq P_{i,t}^{gen}\leq P_{i,\max}^{gen}, \qquad (11)$$

Minimum operation time constraints:

$$t_i^{on}\geq M_i^{on}, \qquad (12)$$

Minimum out of operation time constraints:

$$t_i^{off}\geq M_i^{off}, \qquad (13)$$

Unit Ramp Rate Constraint:

$$\left|P_{i,t}^{gen}-P_{i,t-1}^{gen}\right|\leq Z_{i,\max}, \qquad (14)$$

where, $P^{gen}_{i,max}$ and $P^{gen}_{i,min}$ are the maximum and minimum generation capacity of unit i, in MW. L_t is system load demand at time t, in MW. R_t is system spinning reserve demand at time t, in MW. M_i^{on} is the minimum number of periods unit i, it must remain on operation statue after it has been start-up at time t, in hours. M_i^{off} is the minimum number of periods unit i, it must remain on out of operation statue after it has been shut-down at time t, in hours. t_i^{on} is the continuing number of periods unit i remains on operation statue after it has been start-up at time t, in hours. t_i^{off} is the continuing number of periods unit i must remains on out of operation statue after it has been shut-down at time t, in hours. $Z_{i,max}$ is the maximum ramp rate of unit i, in MW/h.

3 Outline of PSO

PSO algorithm was proposed to solve optimization problems by Kennedy et al. [13], it was a kind of numerical optimization techniques which similarly with genetic algorithm. It is easy to know from the above literature that the forward movement of the particle swarm including the size and direction of the particles were decided based on the original speed, individual and global extreme weighted.

$$v_{j,b+1}=\omega v_{j,b}+\phi_1 c_{rand}\left(q_{j,b}^{best}-x_{j,b}\right)+\phi_2 c_{rand}\left(g_b^{best}-x_{j,b}\right), \qquad (15)$$

where j is index of particles, j=1,2, …, J. b is index for iterations, b=1,2, …, B. $q^{best}_{j,b}$ is the individual best position of particle j in the iteration b. g^{best}_b is the best position of all the particles in the iteration b. $v_{j,b}$ and $x_{j,b}$ are the velocity and location of particle j in the iteration b. ω, ϕ_1 and ϕ_2 are weight coefficients when velocity renewed. c_{rand} is the random number between 0 and 1. The particle swarm will be:

$$x_{j,b+1}=x_{j,b}+v_{j,b+1}. \qquad (16)$$

Each particle in swarm will execute parallel optimazation during the iterations according to its own inertial velocity and the best location in memory, while considering the best location which other particles experienced. Then the best optimization solution will be found through several iterations.

4 CPSO algorithm

The inertial weight of each particle is always set as a relatively large initial value at the beginning of searching process, in order to make the particle moves fast. But this approach obviously has a weak point, which will lead to some particles located at the better location move too large distance to neglect some valuable searching area. If the inertial weight adjusted to a small value at the final stage of searching process, in order to make the particle to do more detail search. But this method will prevent some particles located at the worst location to overtake the other particles. So the same inertial weight value of particle swarm is not appropriation for each particle. The feedback mechanism and closed loop concept are introduced into PSO algorithm in order to overcome the shortcoming described above.

Figure 1 shows a simple input and simple output (SISO) feed back control system, the controlled values $y(t)$ and input values $u(t)$ of object are usually defined as controlled variable and manipulated variable of object respectively. The controlled variable $y(t)$ is fed back through a sensor measurement H and transfer value $h(t)$ to the reference value or set-point $r(t)$.

Each particle actually can be treated as an object. Its dynamic characteristics include current location, fitness value of last iteration and velocity. So the closed loop control system can be built for each particle, the fitness value is defined as controlled variable which is fed back to controller in iterations. Then a new suitable inertial weight will be calculated by controller according to the current fitness of particle and used for renewing the velocity and location.

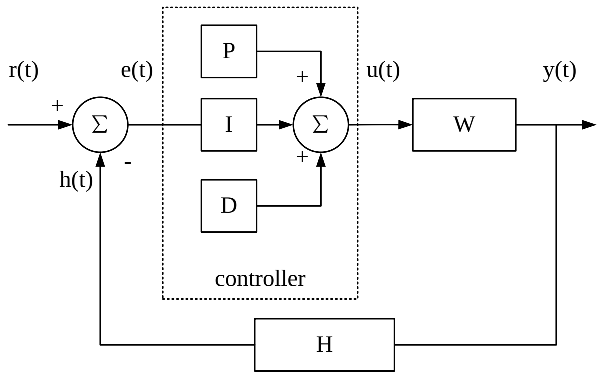

FIGURE 1 Structure of a SISO closed control system.

4.1 STRUCTURE OF PID

PID controller is a control loop feedback mechanism (controller) widely used in industrial control systems and has historically been considered to be the best controller with simple structure and best robustness. So the PID is selected as controller in this CPSO algorithm. There are three separate constant parameters which also be named as three-term control in the PID controller algorithm: the proportional values denoted as P, the integral values denoted as I and derivative values denoted as D, the structure of PID controller is show at Figure 1.

The output value Ξ^{out} which is proportional to the present error value $e(t)$ is produced by the proportional term. The proportional response value can be revised in term of multiplying the current error value through a constant defined as K^{prop}, this term is also named the proportional gain constant. The proportional term is set as follows:

$$\Xi^{out} = K^{prop} e(t). \tag{17}$$

The integral term I^{out} of a PID controller is the sum of the instantaneous error value during the time. This term will supply the accumulated offset value which should have been adjusted previously. The accumulated error term is then multiplied through the integral gain term defined as K^{iteg} and acted to the output value of controller. τ is the variable of integration which takes on values from time 0 to t. The integral term I^{out} is set as follows:

$$I^{out} = K^{iteg} \int_0^t e(\tau) d\tau . \tag{18}$$

The main purpose of the integral term is to accelerate the movement of the object towards the reference value and reduces the residual steady state error term which produced with a pure proportional controller.

The derivative term D^{out} of the object error is calculated through the determining the slope of the error value over the period of the time and multiplying this change magnitude according to the derivative gain constant K^{deri}. The role of the derivative term to the overall responding control action is effected on the basis of the derivative gain constant K^{deri}. The derivative term D^{out} is set as follows:

$$D^{out} = K^{deri} \frac{de(t)}{dt}. \tag{19}$$

The final standard form of the PID controller algorithm is given by:

$$u(t) = K^{prop}\left[e(t) + \frac{1}{T^I}\int_0^t e(\tau)dt + T^D \frac{de(t)}{dt} \right], \tag{20}$$

$$e(t) = r(t) - h(t), \tag{21}$$

where, each parameter has a clear physical meaning in this form. T^I is defined as the integral time constant and T^D is defined as the derivative time constant.

$$K^{iteg} = K^{prop} / T^I , \tag{22}$$

$$K^{deri} = K^{prop} T^D . \tag{23}$$

Sometimes it is useful to rewrite the PID controller in Laplace transform form. It is easy to determine the closed loop transfer function if this form is adopted.

$$G(s) = K^{prop}\left[1 + (1/T^I s) + T^D s\right]. \tag{24}$$

PID controller can be adjusted according to K^{prop}, T^I and T^D, these parameters are constructed as gain vector.

4.2 DEFINITION OF CPSO

There are J numbers of particles in whole swarm. W_j is the j particle, j=1,2, …, J. The manipulation variable u_j is defined as inertia weight factor. The output value of object is y_j defined as the fitness value of last iteration. H_j is the transfer function of feed back tunnel. It is also named as measurement sensor. Its output value is h_j. These parameters are given by the following equations:

$$u_j = \omega_j\,, \tag{25}$$

$$H_j = \varepsilon\left|1/y^{ave}\right|, \tag{26}$$

$$h_j = H_j y_j = \varepsilon\left|y_j / y^{ave}\right|, \tag{27}$$

where, ε is adjust factor and generally to be set as 1. y^{ave} is average value of current fitness for all particles. The parameter h_j is the evaluation term for particle W_j. The particle can be treated as a relative optimization location if h_j is larger than 1, on the contrary the particle is considered as lag location. The reference value is set as 1, and then the error term e_j is given as follows:

$$e(t) = r(t) - h(t) = 1 - \varepsilon\left|y_j / y^{ave}\right|. \tag{28}$$

The ζ is defined as gain vector of PID controller for j particle.

$$\zeta = \left[K_i^{prop}, \quad T_i^I \quad, T_i^D\right]^T = \left[-1, \quad \Re^{ite}/20, \quad 0\right]^T. \tag{29}$$

The gain proportion parameter K_i^{prop} will to be set lower than zero, because the movement magnitude of the particle which traps into local extreme value needs to be given larger inertia weight. The particle at a relatively optimization position need to be given a smaller inertia weight, in order to do more meticulous searching. Because the stability error will be introduced if the controller just include the proportion module, so the integral term should be added into the controller to eliminate the error term. The integral time constant T_i^I means it can play the same role as proportion term past T_i^I time. The specific problem is that the excess overshooting will be shown if integrator term is added into PID controller. Further more the integral windup will be caused. Some measures must be adopted to prevent this phenomenon. There is a simple anti integrator windup strategy for control PSO is given as follows:

$$T_i^I = \begin{cases} \Phi^{ite}/20, & \delta_j^{low} < \omega_j < \delta_j^{up} \\ 0, & \omega_j = \delta_j^{low} or \omega_j = \delta_j^{up} \end{cases}, \tag{30}$$

$\delta_j^{\ low}$ and $\delta_j^{\ up}$ are low and up limit of inertia weight ω_j. Φ^{ite} is the maximum iteration number. Because inertia weight and particle search area ranges are predefined between bounded set. Therefore, the output variables which are fitness value of the particle are bounded, the situation does not appear divergent. That means the closed-loop stability is guaranteed.

There will be more effective control if the derivative term added into controller, but at the same time the probability of unstable statute is also increased, so the derivative time constant is defined as zero in CPSO.

4.3 SOLVING STEP OF CPSO

The solving step of control PSO is as follow.

Step 1: Initialize the particles swarm and the initial iteration number φ_i is set as zero.

Step 2: Iteration calculation of particles.

Step 3: Renew the current individual particle best position $q_{best,j}$, the current best position g_{best} of all the particles swarm and the fitness value.

Step 4: If the iteration number φ_i does not reache the maximum iteration number Φ^{ite}, then the inertia weight ω is calculated through:

$$\omega = K^{prop}\left[1 + \left(1/T^I s\right) + T^D s\right]e. \tag{31}$$

Iteration calculation of particles by using new inertia weight ω, iteration number φ_i increases as follows:

$$\varphi_i = \varphi_i + 1. \tag{32}$$

Go to Step 2.

Step 5: If the iteration number φ_i reaches the maximum iteration number Φ^{ite}, then the evolution stops and the best position value is outputted.

5 Solving unit commitment problem under emissions reduction

5.1 CODING METHOD

The generation of all the units in different period will be connected as an individual of CPSO and represented by $N \times T$ matrix. This matrix is shown as follows:

$$P_k^{gen} = \left(Q_1 \quad , \quad Q_2 \quad , \quad \cdots \quad , \quad Q_t \quad , \quad \cdots \quad , \quad Q_T\right) =$$
$$\left(R_1 \quad , \quad R_2 \quad , \quad \cdots \quad , \quad R_i \quad , \quad \cdots \quad , \quad R_N\right)^T =$$
$$\begin{bmatrix} P_{1,1}^{gen} & P_{1,2}^{gen} & \cdots & P_{1,t}^{gen} & \cdots & P_{1,T}^{gen} \\ P_{2,1}^{gen} & P_{2,2}^{gen} & \cdots & P_{2,t}^{gen} & \cdots & P_{2,T}^{gen} \\ \vdots & \vdots & & \vdots & & \vdots \\ P_{i,1}^{gen} & P_{i,2}^{gen} & \cdots & P_{i,t}^{gen} & \cdots & P_{i,T}^{gen} \\ \vdots & \vdots & & \vdots & & \vdots \\ P_{N,1}^{gen} & P_{N,2}^{gen} & \cdots & P_{N,t}^{gen} & \cdots & P_{N,T}^{gen} \end{bmatrix} \tag{33}$$

where, P_k^{gen} is the k individual of particles swarm. $P_{i,k}$ is element of the i row and t column in the coding matrix, it represents the generation of unit i during the period t. Q_t is the t column vector in the coding matrix, it represents the unit statute of all units during the one period of all dispatch times, this vector can be used to calculate the cost of production and economic dispatch. R_i is the i row vector in the coding matrix, it represents the start-up and shut-down statute of all units during the all dispatch periods, this vector can be used to calculate the cost of start-up and shut-down for unit, but it must satisfy the minimum operation time constraints or out of operation time constraints.

The operation status of unit is decided by the element of matrix, furthermore the start-up or shut-down status is decided according to the generation of unit, this is given as following:

$$\eta_i(t)=\begin{cases}0, & P_{i,t}^{gen}=0\\ 1, & others\end{cases}. \quad (34)$$

Velocity matrix of CPSO algorithm is set as follows, where, V_k^{gen} is the velocity component of element P_k^{gen} in the particles swarm.

$$V_k^{gen}=\begin{bmatrix} V_{1,1}^{gen} & V_{1,2}^{gen} & \cdots & V_{1,t}^{gen} & \cdots & V_{1,T}^{gen}\\ V_{2,1}^{gen} & V_{2,2}^{gen} & \cdots & V_{2,t}^{gen} & \cdots & V_{2,T}^{gen}\\ \vdots & \vdots & & \vdots & & \vdots\\ V_{i,1}^{gen} & V_{i,2}^{gen} & \cdots & V_{i,t}^{gen} & \cdots & V_{i,T}^{gen}\\ \vdots & \vdots & & \vdots & & \vdots\\ V_{N,1}^{gen} & V_{N,2}^{gen} & \cdots & V_{N,t}^{gen} & \cdots & V_{N,T}^{gen}\end{bmatrix}. \quad (35)$$

5.2 FITNESS FUNCTION

The objective function of unit commitment optimization under emissions reduction is set as fitness function of CPSO algorithm. The lowest fitness value means the lowest operation cost, moreover it is the best solution.

5.3 INDIVIDUAL STRATEGY ADJUSTMENT

Because the individual particle may not satisfy the constraint conditions after initialization or renewable, so the individual particle needs to be adjusted in order to meet the constraints. The procedure is given as follows.

5.3.1 Reduce Dimension

Unit commitment is a high dimension optimization problem. The dimension is reduced in the searching process by using the implicit information through mining the constraints. The minimum number of operation unit during the period t is given by spinning reserve constraints Equation (10). And only the previous χ unit during period t under the operation status according to the priority sorting, that means the following constraint is satisfied:

$$P_k^{gen}\ge P_{i,\min}^{gen},\ 1\le i\le \chi . \quad (36)$$

The Equation (37) also can be obtained according to the power balance constraints Equation (9) and up and down generation constraints of unit Equation (11):

$$\sum_{i=1}^{N} P_{i,\min}\eta_{i,t}\le L_t \quad (37)$$

There are γ units are out of operation during t, moreover, it means the maximum number of operation unit can also be obtained according to Equation (37). So only χ+1 to N-γ status *for* element $P_{i,t}^{gen}$ of matrix P_k^{gen} needs to be optimization:

$$P_{i,t}^{gen}=0,\ N-\gamma+1\le i\le N . \quad (38)$$

5.3.2 Constraints Handling

The individual of particle swarms adjusted to meet the constraints will be implemented as follows:

(i) Adjust the components of location matrix in order to make it meet the generation constraints of units, according to the (39).

(ii) Adjust the start-up and shutdown status of units to satisfy the spinning constraints. If the sum of maximum generation of units under the operation status is lower than the sum of total load and spinning at current time, then the units under the out of operation status while meet the minimum out of operation time constraints need to be start-up, in accordance with the order of priority until the total generation reaches the requirement of system. The unit start-up order of priority is decided according to the literature (S. Dekrajangpetch et al.) [5], it means the units which have the lower incremental rate of cost will be set as the higher priority level. On the contrary, the units will be treated as lower priority level.

$$P_{i,t}^{gen}=\begin{cases} P_{i,\max}^{gen} & P_{i,t}^{gen}\ge P_{i,\max}^{gen}, i\ge N-\gamma,\\ & \quad t_i^{on}\ge M_i^{on}\ or\ \ t_i^{off}\ge M_i^{off}\\ P_{i,t}^{gen} & P_{i,\min}^{gen}\le P_{i,t}^{gen}\le P_{i,\max}^{gen}, i\ge N-\gamma,\\ & \quad t_i^{on}\ge M_i^{on}\ or\ \ t_i^{off}\ge M_i^{off}\\ P_{i,\min}^{gen} & P_{i,t}^{gen}\le P_{i,\min}^{gen}, i\ge N-\gamma,\\ & \quad t_i^{on}\ge M_i^{on}\ or\ \ t_i^{off}\ge M_i^{off}\\ 0, & \quad otherwise\end{cases}. \quad (39)$$

(iii) The total generation of all units probably not equals the total load demand during some periods. So the load needs to be adjusted. If the total technology generation of units under operation status is larger than the total load at current time, then these units which satisfy the minimum operation time constraints need to be shutdown according to the priority sorts.

(iv) If the total generation is lower than the total demand at current time, then the generation of units needs to be increased, in order to meet the power balance constraints. If the total generation is larger than the total demand at current time, then the generation of units under operation status should be reduced. But the ramp rate constraints and generation constraints of unit must be satisfied in the process of adjustment.

Some problems may be appeared after the above adjustment of individual. Furthermore, the total maximum of technology generation of units under operation status is still lower than the sum of total demand and spinning reserve at current period. Because the demand increases so fast, which induced by some units were shut-down during some periods, but this units cannot start-up according to the change of demand for minimum start-up time constraints. So the shut-down decision of units need to be re-evaluated before this period, the shutdown decision should be replaced by reducing the technology generation of units, while satisfy the power balance constraints.

6 Simulation and analysis

The 9 units system is used to test the proposed method. The main parameters are given as following tables. Table 1 and Table 2 show the unit system data. The result of economic dispatch of unit commitment is shown as Table 3. The emission quantities of three different dispatch models are shown as Figure 2. The first scene represents the objective function is set as minimum economic dispatch and the average emission quantity is 346.7458lb, this is the highest scene. The second scene represents the objective function is set as minimum emission dispatch and the average emission quantity is 279.9292lb, this is the lowest scene.

TABLE 1 9-units system data (Unit cost data and emission data)

Unit	ρ_i($/h)	μ_i($/MWh)	φ_i($/MW^2-h)	Start cost($)	α_i(lb/h)	β_i(lb/MWh)	γ_i(lb/MW^2-h)
1	142.735	10.6940	0.00643	200	24.300	0.81	0.0036
2	230.00	19.1000	0.00712	115	27.023	0.10	0.0035
3	81.136	13.3272	0.00876	80	27.023	0.50	0.0330
4	81.298	13.3538	0.00895	80	22.070	0.30	0.0034
5	218.335	18.1000	0.00612	100	24.300	0.81	0.0380
6	87.136	19.3272	0.01036	80	29.040	0.03	0.0034
7	118.821	37.8896	0.01433	30	29.030	0.02	0.0039
8	128.821	39.8896	0.01633	30	27.050	0.02	0.0030
9	187.364	49.3272	0.02436	70	22.070	0.30	0.0034

TABLE 2 9-units system data (Unit operation data)

Unit	Up(h)	Down(h)	Initial(h)	R_{up}(MW/h)	R_{down}(MW/h)	P_{max}(MW)	P_{min}(MW)
1	5	3	5	78	78	155	54
2	4	2	-3	50	50	100	25
3	3	2	3	38	38	76	15
4	3	2	3	38	38	76	15
5	4	2	-3	50	50	100	25
6	3	2	3	25	25	50	10
7	1	1	-1	20	20	20	4
8	1	2	-1	20	20	20	4
9	3	2	3	25	25	50	10

TABLE 3 The results of unit commitment under different scenes

Hour	Scene1(Units 1-9)	Scene2(Units 1-9)	Scene3(Units 1-9)	Load(MW)	θ_{ec}($/lb)
1	101 110 000	110 101 001	111 101 000	355	17.78
2	101 110 000	110 101 001	111 101 000	327	8.07
3	101 110 000	011 111 001	111 101 000	309	8.07
4	101 110 000	011 111 001	111 101 000	290	8.07
5	101 110 000	010 111 001	101 100 000	281	8.07
6	101 110 000	010 111 001	101 100 000	281	8.07
7	101 110 000	011 111 001	101 100 000	290	8.07
8	111 100 000	110 101 001	101 110 000	318	8.07
9	111 110 000	110 101 001	111 110 000	364	17.78
10	111 110 000	110 101 001	111 110 000	400	17.78
11	111 110 000	110 101 111	111 110 000	409	27.63
12	111 110 000	110 101 111	111 111 000	414	27.63
13	111 110 000	110 101 111	111 101 000	409	27.63
14	111 110 000	110 101 001	111 101 000	400	17.78
15	111 110 000	110 101 101	111 101 000	396	17.78
16	111 110 000	110 101 111	111 101 000	396	17.78
17	111 110 000	110 101 111	111 101 000	414	27.63
18	111 110 000	111 101 111	111 111 000	455	27.63
19	111 110 000	111 101 111	111 111 000	450	27.63
20	111 110 000	111 101 111	111 111 000	441	27.63
21	111 110 000	111 111 111	111 111 000	428	27.63
22	111 110 000	110 111 111	111 101 000	418	27.63
23	111 110 000	110 111 111	111 101 000	396	17.78
24	101 110 000	010 111 111	111 101 000	368	17.78

The fuel cost of three different dispatch models are shown as Figure 3, the first scene represents the objective function is set as minimum economic dispatch and the average fuel cost is $5861.38, this is lowest scene. The second scene represents the objective function is set as minimum emission dispatch and the average cost is $9345.38, this is the highest scene. The third scene represents the objective function is set as comprehensive dispatch of unit commitment and the average cost is $6227.13, this scene is interposed between the two cases described in the foregoing. All these problems are solved by control PSO algorithm. The total cost of three different dispatch models are shown as Figure 4, the first scene represents the objective function is set as minimum economic dispatch and the average cost is 12687.7625$, this is interposed between the scene1 and scene 2.

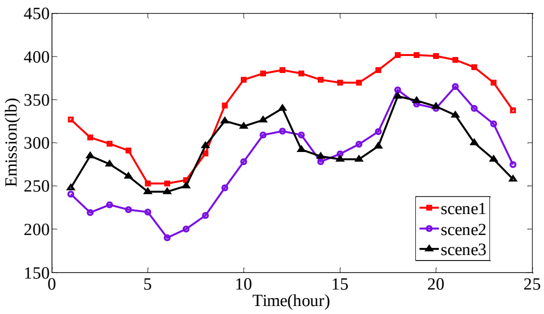

FIGURE 2 The emissions under different dispatch models by CPSO

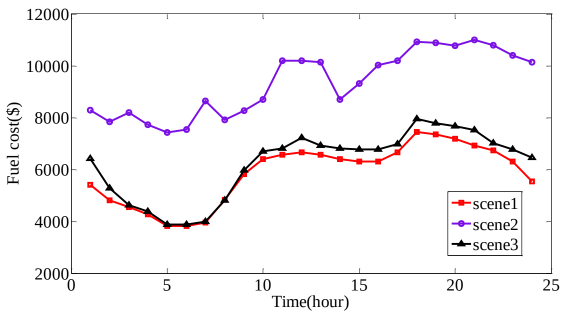

FIGURE 3 The fuel cost under different dispatch models by CPSO

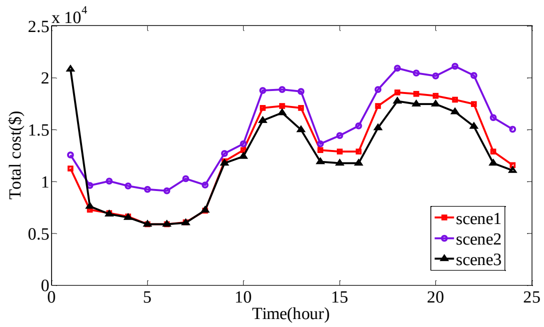

FIGURE 4 The total cost under different dispatch models by CPSO

The second scene represents the objective function is set as minimum emission dispatch and the average cost is $14954.04, it is the highest scene. The third scene represents the objective function is set as comprehensive dispatch of unit commitment and the average cost is $11918.88, it is lowest. Above results show that the total cost will increase so fast if too emphasize the emission reduction, so the relatively balance approach considering the emission reduction and economic dispatch together is needed.

Figure 5 shows the results distribution of total cost of comprehensive unit commitment under emission reduction by different algorithms including PSO, GA, and CPSO. Continuous simulating 30 times, the best solution of PSO is $286882.55, the worst solution of PSO is $294377.14. The deviation of the worst solution with respect to the best solution is 2.91%, and about 53.4% solution deviates from the best solution is lower than 1.5%.

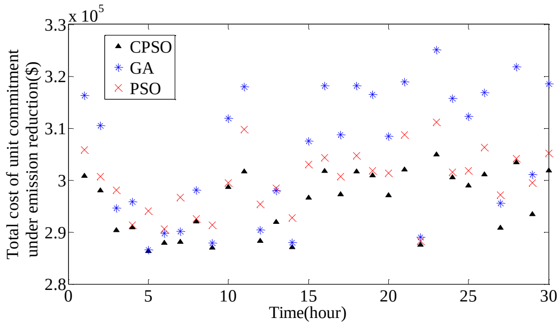

FIGURE 5 The results distribution of total cost of comprehensive unit commitment under emission reduction through different algorithms

The best solution of GA is $286682.31, the worst solution of GA is £305275.76. The deviation of the worst solution with respect to the best solution is 6.34%, and about 26.3% solution deviates from the best solution is lower than 1.5%. The best solution of CPSO is $286253.24, the worst solution of CPSO is $291573.82, the deviation of the worst solution with respect to the best solution is 1.93%, and about 76.7% solution deviates from the best solution is lower than 1.5%. So the robustness and precise of CPSO are obviously best than the other algorithms.

7 Conclusions

There are following conclusions according to the simulation:

(i) The objective function considering the minimum cost and minimum emission targets together is more reasonable to discuss the unit commitment problem, because the environmental factor has same important role as economic factor.

(ii) The emission price factor is introduced into the model, this will helpful to transfer the multi-objective optimization problem to the single-objective optimization problem.

(iii) The total cost will increase so fast if too emphasize on the role of emission reduction, so the balance need to be selected between the target of economic and emission.

(iv) CPSO algorithm shows robustness and precise than the other algorithms.

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