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Original Research Paper

# Environmental Economic Dynamic Dispatch Modelling and Simulation Including Wind Farms

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## ABSTRACT

Large-scale integration of wind power has brought profound challenge to traditional power generation dispatch. It becomes necessary to effectively coordinate the operation of wind power and traditional power sources. Traditional economic dispatch to minimize the fuel cost no longer meets the need for environmental protection when emission reduction is mandatory. Based on the optimal dispatch in traditional power system, the concept of "energy-environmental efficiency" was introduced to modify the optimal dispatch model in wind power integrated system, and the multi-objective optimal dispatch model was proposed on the basis of comprehensively considering the minimum of the resource consumption, the best energy-environmental efficiency and the highest system stability. A hybrid particle swarm and simulated annealing optimization algorithm with fuzzy technology was presented to solve the optimization model. Compared with traditional economic dispatch, the model proposed in this paper is reasonable and can better protect the ecological environment.

## INTRODUCTION

Conventional energy is given priority to with coal, oil, natural gas; this non-renewable energy causes serious air pollution. With the energy crisis and environmental pollution increasingly severe, development and utilization of wind energy has already been paid high attention by the countries all over the world (Sinha et al. 2003, Li & Jiang 2011). Wind power is a kind of "$CO_2$ zero emission" renewable energy, to develop wind power system can optimize the power structure, and promote low-carbon electricity production (Chen Chun-Lung 2008, Kuo 2010).

Traditional power system economic dispatch (ED) model aiming at power generation costs the least and does not take into account environmental pollution produced by power production. It also does not take into account factors such as energy and environment efficiency and ignores the low carbonization of electric power system. Electric power industry is the main force of our country's $CO_2$ emissions. Therefore, at present increasingly serious environmental problems and energy crisis, under the premise of large wind farms parallel operation, it is of great significance for sustainable development how to realize $CO_2$ effective emissions reduction of electric power industry by optimizing the scheduling.

In this paper, focusing on the economy at the same time considering the low carbonization of power production, introducing the concept of "energy and environmental economic benefits" to the optimal scheduling problem of power systems, which contains wind farms, environment economic dynamic scheduling model is established (Hetzer & Yu 2008). Due to the enormous number of dimensions and complexity of the solution of the proposed model, the maximum fuzzy satisfaction degree method and the improved particle swarm combined with simulated annealing thought are adopted to calculate, to gain a higher quality solutions. The simulation results verify that the scheduling model constructed in this paper is reasonable and the algorithm is feasible (Pappala et al. 2009).

## ENVIRONMENTAL/ECONOMIC DYNAMIC DISPATCH MODELLING INCLUDING WIND FARMS

### Objective Functions

Thermal power generation resource consumption is the most important economic indicators to measure power production costs and is also the core of traditional power system scheduling problems. Its expression is:

$$\min F_1 = \min[\sum_{t=1}^{T}\sum_{i=1}^{G}(f_{it}(P_{it}) + (1 - I_{it-1})S_{it})I_{it}] \qquad ...(1)$$

Where, $F_1$ is the power generation resources consumption cost; $T$ is the hour number of scheduling period, this paper takes $T$ = 24; G is the number of thermal power stations involved in optimizing; $P_{it}$ is the generator active power of unit i at time $t$; $I_{it}$ is the running state of unit $i$ at time $t$; if $I_{it}$ is equal to 1, which means the running state is running; if

$I_{it}$ is equal 0, which means the running state is downtime; $f_{it}(P_{it})$ is the run energy consumption of conventional unit *i* in period *t*, and its expression is:

$$f_{it}(P_{it}) = a_i + b_i p_{it} + c_i p_{it}^2 \quad ...(2)$$

Where, $a_i$, $b_i$, $c_i$ are run energy consumption characteristic parameters. $S_{it}$ is unit start-up costs in time *t*, it is related to the length of the downtime $\tau_i$, $S_{it}$ is expressed by the following general formula:

$$S_{it} = d_i + s_i(1 - e^{-T_{it}^{off}/t_i}) \quad ...(3)$$

Where, $\delta_i$, $\sigma_i$, $\tau_i$ are start-up costs coefficients of the unit *i* (Liu & Xu 2010), $\tau_{it}^{off}$ is the unit *i* outage time at time *t*.

Thermal power plants' maximum allowable emission concentrations of various polluting gases are given in Table 1. $SO_2$ and $NO_x$ will be converted into an equivalent $CO_2$ emissions concentration (Azizipanah-Abarghooee et al. 2012).

$$(C_{CO_2})_e = (C_{CO_2}) + 700(C_{SO_2}) + 1000(C_{NO_x}) \quad ...(4)$$

Where, $(C_{CO_2})_e$ is the translated equivalent $CO_2$ emission concentration, kg/m$^3$.

The equivalent $CO_2$ emissions are defined, its expression is:

$$E_{CO_2} = \frac{(C_{CO_2})_e V}{M} \quad ...(5)$$

Where, *V* is the unit fuel combustion emission pollution gas volume, m$^3$; M is unit fuel, kg; $E_{CO_2}$ is the equivalent $CO_2$ emissions ratio; it is a constant, whose numerical value is related to the fuel of concrete used in thermal power plants.

In order to analyze different working conditions of thermal power energy and environmental efficiency, considering the function of the power generation efficiency $h_e$ and thermal power generation active power $P_{it}$, energy and environmental efficiency indicators are built:

$$e_{eve} = \frac{h_{ie} h_r(P_{it}) q_a}{h_{ie} h_r(P_{it}) q_a + KE_{CO_2}} \quad ...(6)$$

Where, $\eta_{ie}$ is the *i*-station thermal power generation efficiency; $q_\alpha$ is fuel calorific value, MJ/kg; *k* is the heat loss coefficient caused by pollutant emission, MJ/kg; generally we take $K = 2$.

$h_r(P_{it})$ is the function relational expression of the power generation efficiency $h_{ie}$ with active power $P_{it}$, the expression is:

$$h_r(P_{it}) = g_i + b_i P_{it} + a_i P_{it}^2 \quad ...(7)$$

Where, $a_i$, $b_i$, $g_i$ are the efficiency functional relationship coefficients.

Table 1: Maximum admissible concentration for some harmful gases in the atmosphere of the work place.

| Harmful gases | Average value (mg/m$^3$) | Maximum admissible concentration (mg/m$^3$) |
|---|---|---|
| $CO_2$ | 7000 | 10000 |
| $SO_2$ | 10 | 15 |
| $NO_x$ | - | 10 |

The environmental economic dynamics model built in this paper is:

$$\max F_2 = \max_{t \in T} \sum_{i=1}^{G} \frac{h_{ie} h_r(P_{it}) q_a^i}{h_{ie} h_r(P_{it}) q_a^i + 2E_{CO_2}^i} \quad ...(8)$$

Environmental and economic dynamics model represents the sum of energy environmental efficiency indicators of all the running generators at time *t*, it is used to illustrate the pollution degree of ecological environment caused by the production of electrical energy per unit time the energy consumed. The bigger its value is, the better period efficiency energy environment is.

### Constraints

**Equality constraint:** Constraint conditions include equality constraints and inequality constraints; equality constraint is the system power balance constraints. If the network loss is ignored, equality constraint representation is as follows:

$$\Delta P_i = \sum_{i=1}^{G} P_{it} + \sum_{m=1}^{M} P_{wm \cdot t} - P_{D \cdot t} = 0 \quad ...(9)$$

Where, M is the unit's number of wind generator system; $P_{wm \cdot t}$ is the active power output of wind turbine *m* at the $i^{th}$ time; $P_{D \cdot t}$ is the system load values in the period *t*.

**The unit output constraints:** Conventional generator sets maximum and minimum output constraint is:

$$P_{t,\min} \le P_t \le P_{t,\max}, i = 1, \mathbf{L}, G \quad ...(10)$$

Where, $P_{t,\min}$, $P_{t,\max}$ are the minimum and maximum output of conventional unit *i*.

Conventional generator output is the control variable, the inequality constraints can be met by regulating the control variable itself, namely:

$$P_{i,t} = \begin{cases} P_{t,\min}, P_{i,t} < P_{t,\min} \\ P_{t,\max}, P_{i,t} > P_{t,\max} \end{cases} \quad ...(11)$$

**Conventional generators ramp rate constraints**

$$\begin{cases} P_{i,t-1} - P_{i,t} - D_{Ri}\Delta T \le 0 \\ P_{i,t} - P_{i,t-1} - D_{Ri}\Delta T \le 0 \end{cases}, i = 1, \mathbf{L}, G \quad ...(12)$$

Where: $P_{i,t}$ is the output of conventional unit *i* in the current period; $P_{i,t-1}$ is the output of conventional unit $i$ in a previous period; $U_{Ri}$, $D_{Ri}$ are respectively an upper and a lower ramp rate of conventional unit $i$; $\Delta T$ is the scheduling time intervals.

**The system spinning reserve constraint**: Because of the wind power provides only energy, and it does not provide spare capacity, so the system of spinning reserve is the spinning reserve that thermal power unit can provide. That is:

$$\sum_{i=1}^{G}(P_{i\max}^{t}-P_{i}^{t})\geq h_{1}P_{Dup}^{t} \quad ...(13)$$

$$\sum_{i=1}^{G}(P_{i}^{t}-P_{i\min}^{t})\geq h_{2}P_{Ddown}^{t} \quad ...(14)$$

Where, $h_1$ and $h_2$ are the upper and lower rotating standby rate of the system; $P^t_{Dup}$ and $P^t_{Ddown}$ were the total system load corresponding to the upper and lower standby; $P^t_{imax}$ and $P^t_{imin}$ were output upper and lower limits of unit $i$ at time $t$.

**Generator start and outage time constraints, i.e.**

$$\begin{aligned}&(I_{it}-I_{i(t-1)})\times\sum_{j=t-T_{i\min}^{off}}^{t-1}(1-i_{ij})\geq T_{i\min}^{off}\\&(I_{i(t-1)}-I_{it})\times\sum_{j=t-T_{i\min}^{off}}^{t-1}(1-i_{ij})\geq T_{i\min}^{on}\end{aligned} \quad ...(15)$$

Where, $T_{i\min}^{off}$ and $T_{i\min}^{on}$ are respectively the minimum outage time and minimum boot time of the generator $i$.

Environment economic dynamic scheduling model is built in this paper to better balance the economics and environmental benefits of electricity production, and it can evaluate different units of generating resource utilization efficiency, which is in accord with the current power system low carbonization development goals.

## ENVIRONMENTAL ECONOMIC DYNAMIC SCHEDULING MODEL FUZZY PROCESSING

Two objective functions of environmental economic dynamic scheduling model are conflicting; generally there is no absolute optimal solution. The biggest satisfaction method of fuzzy mathematics is used to convert multiple objective functions into a single objective function to evaluate resource consumption minimization objective belonging to cost function (Hota et al. 2010), that is, the smaller is it, the more priority of the objective is. Energy environment efficiency optimization objective belongs to quality-benefit type functions, that is, the greater is it, the more priority of the objective is. Descending half linear shape is chosen for the resource consumption targets membership function; rising half linear shape is chosen for the energy environmental benefits targets membership function, the mathematical expression is as follows:

$$m(F_1)=\begin{cases}1 & F\leq c_{01}\\ \dfrac{c_{01}+d_{01}-F}{d_{01}} & c_{01}<F\leq c_{01}+d_{01}\\ 0 & F>c_{01}+d_{01}\end{cases} \quad ...(16)$$

$$m(F_2)=\begin{cases}1 & F\leq c_{01}\\ \dfrac{E_e+c_{02}+d_{01}}{d_{02}} & c_{02}-d_{02}<E_e<c_{02}\\ 0 & E_e>c_{02}-d_{02}\end{cases} \quad ...(17)$$

Where, $C_{01}$ and $C_{02}$ are respectively single-objective optimization targets of minimal consumption of resources and optimum energy and environmental benefits; $\delta_{01}$ is acceptable resource consumption value added; $\delta_{02}$ is the energy and environmental efficiency values expected to improve.

Satisfaction degree $l$ is defined as:

$$l=\min\{m(F_1),m(F_2)\} \quad ...(18)$$

Get fuzzy processing mathematical expressions:

$$\min\{\max\left|m_m-m\left(F_m\left(x\right)\right)\right|\},m=1,2 \quad ...(19)$$

$$s.t\begin{cases}m(F_m(x))\geq m_{rm} & m=1,2\\ \text{Equation}\left(4\right)-\left(10\right)\end{cases} \quad ...(20)$$

Where: $\mu_m$ is the reference membership values expected to achieve.

## SIMULATED ANNEALING PARTICLE SWARM OPTIMIZATION (PSO-SA)

**Standard PSO:** Particle swarm optimization (PSO) is an evolution computing technology based on swarm intelligence, which was proposed by Eberhart and Kennedy in 1995, and it is based on the simulation of the flock. The principle is described as follows: A flock of birds search food randomly in a region where there is only a piece of food. The most simple and effective strategy to find food is to search the area around the nearest bird from food, which constitutes one of the basic concepts of the PSO (Agrawal et al. 2008). Assuming that a community is composed of $n$ particles in a D-dimensional search space, wherein $x_i = (x_{i1}, x_{i2}, ... x_{id})$ , $i$ = 1, 2, ..., $n$, is the position of $i^{th}$ particle in D-dimension. Fitness value can be calculated by substituting $X_i$ into an objective function, and the pros and cons of $X_i$ can be obtained according to the size of the fitness value. "Flying" velocity of the particle $i$ is a D-dimensional vector, denoted as $v_i = (v_{i1}, v_{i2}... v_{id})$. $P_i = (p_{i1}, p_{i2},..., p_{id},)$ is the best position of particle $i$ searched, corresponding to the optimal solution particle $i$ found by itself, which is the location of the best fitness value. Optimal position for the entire particle swarm search after the h^th^ iteration is $P_{igd} = (P_{i1}, P_{i2}... P_{id})$. By the above definition, the standard formula of PSO can be expressed as:

$$V_{id}^{(k+1)} = wv_{id}^{(k)} + c_1 r_1^{(k)}(p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2^{(k)}(p_{gd}^{(k)} - x_{id}^{(k)}) \quad ...(21)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + V_{id}^{(k+1)} \quad ...(22)$$

Where, $i$ is the number of particles in the swarm; $d$ represents the d^th^-dimension of particles; ω is the inertia weight coefficient; $r_1$, $r_2$ are the random values between [0, 1]; $c_1$, called cognitive factor, represents belief degree on experience, which can be used to adjust the step size of particles to fly towards the direction of its local best position; $c_2$, known as the coefficient of social learning, represents the belief degree on individuals around, which can be used to adjust the step size of particles to fly towards the direction of its global best position. The algorithm iteration termination condition is generally chosen as the maximum number of iterations or fitness value which satisfies the predetermined threshold value of the minimum fitness after searching the optimal location.

Inertia weight calculation expression is as follows:

$$w(k) = (\frac{k-1}{K-1})^a (w_f - w_i) + w_i \quad ...(23)$$

Where, α is the index; $k$ is the number of iterations; $K$ is the threshold of iteration times; $w_f$ is the inertia weight coefficient that the number of iterations reaches a threshold value; $w_i$ is the initial inertia weight coefficient.

### Simulated Annealing

**Metopolis guidelines**: Metopolis guidelines define the probability of the internal energy of the object under a certain temperature $T$ from the state $i$ to state $j$, which is defined as follows:

$$P_{ij}^T = \begin{cases} 1, & E(j) \le E(i) \\ e^{-(\frac{E(j)-E(i)}{KT})} = e^{-(\frac{\Delta E}{KT})}, & others \end{cases} \quad ...(24)$$

Where, $e$ is the natural logarithm, $E(i)$ and $E(j)$ respectively denote the internal energy of the solid under state $j$ and $i$, $\Delta E = E(j) - E(i)$, which means the internal energy increment, $K$ is the Boltzmann constant.

**SA algorithm (SA):** Simulated annealing algorithm is a kind of overall optimization algorithm simulated annealing process of solid, in the process of search it has the probabilistic jumping ability, and it can effectively avoid the search process fall into local optimal. The algorithm not only accepted during the annealing good solution, but also accept the inferior solution with a certain probability, and this probability is controlled by the temperature parameters, the size of which decreases as the temperature dropped.

This paper introduces the idea of the simulated annealing into particle swarm optimization algorithm, the velocity and position of each particle update process is added mechanism of simulated annealing. Metopolis Standards is adopted to update optimal solution of the particle swarm fitness value after evolutionary, and inferior solutions ar accepted in accordance with formula (18) probability formula.

$$P = exp(-\Delta E / T) \quad ...(25)$$

$$\Delta E = \frac{f(S_n) - f(S)}{f(S_n)} \quad ...(26)$$

Where, P is inferior solution probability of being accepted in each iteration process; $DE$ solution for the old and the new fitness function values change; $T$ is the annealing temperature; and $f(S_n)$ and $f(S)$ are respectively the old and the new fitness function values in the iterations process.

Annealing method used in this paper is:

$$T_{k+1} = a \times T_k \quad ...(27)$$

Where, α is the annealing coefficient, $0 < \alpha < 1$.

### PSO-SA Algorithm Calculation Process

PSO algorithm adopts a parallel search, convergence is faster, parameters required to adjust are less, easy to implement,

Table 2: Load data.

| | | | | |
|---|---|---|---|---|
| Time | 1 | 2 | 3 | 4 |
| Load/pu | 3.297 | 3.108 | 2.961 | 2.913 |
| Time | 5 | 6 | 7 | 8 |
| Load/pu | 2.957 | 3.055 | 3.648 | 4.243 |
| Time | 9 | 10 | 11 | 12 |
| Load/pu | 4.679 | 4.737 | 4.646 | 4.648 |
| Time | 13 | 14 | 15 | 16 |
| Load/pu | 4.613 | 4.587 | 4.636 | 4.632 |
| Time | 17 | 18 | 19 | 20 |
| Load/pu | 4.877 | 4.932 | 4.928 | 4.734 |
| Time | 21 | 22 | 23 | 24 |
| Load/pu | 4.486 | 4.089 | 3.609 | 3.107 |

Table 3: Wind power data.

| | | | | |
|---|---|---|---|---|
| Time | 1 | 2 | 3 | 4 |
| $P_W$/pu | 0.160 | 0.168 | 0.165 | 0.178 |
| Time | 5 | 6 | 7 | 8 |
| $P_W$/pu | 0.185 | 0.156 | 0.161 | 0.169 |
| Time | 9 | 10 | 11 | 12 |
| $P_W$/pu | 0.147 | 0.142 | 0.159 | 0.189 |
| Time | 13 | 14 | 15 | 16 |
| $P_W$/pu | 0.166 | 0.185 | 0.186 | 0.193 |
| Time | 17 | 18 | 19 | 20 |
| $P_W$/pu | 0.174 | 0.187 | 0.159 | 0.187 |
| Time | 21 | 22 | 23 | 24 |
| $P_W$/pu | 0.191 | 0.187 | 0.172 | 0.149 |

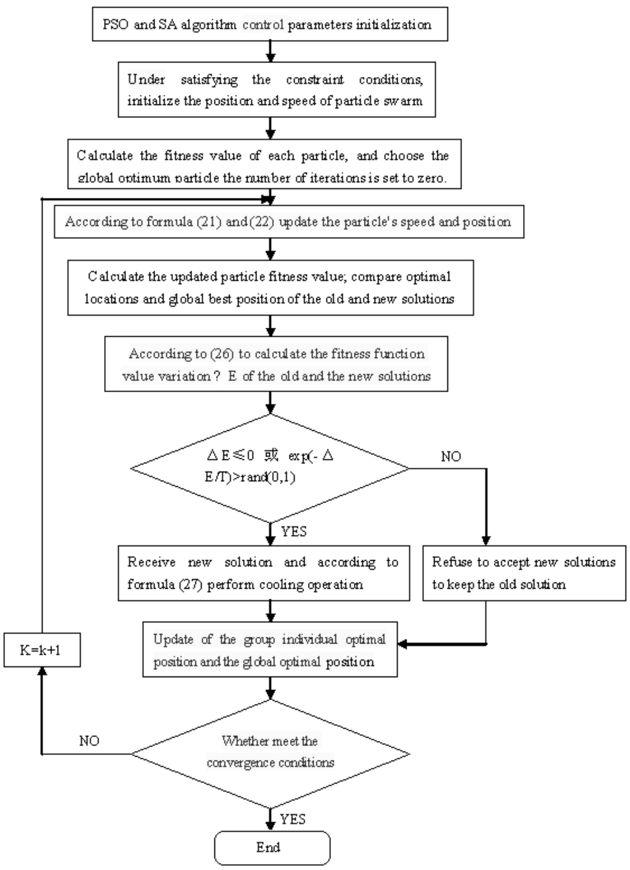


Fig. 1: PSO-SA calculating process.

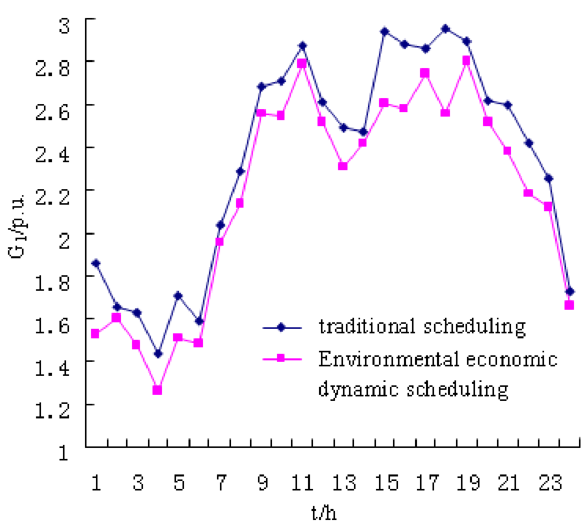


Fig. 2: The daily output curve of unit 1 under the two methods of scheduling.

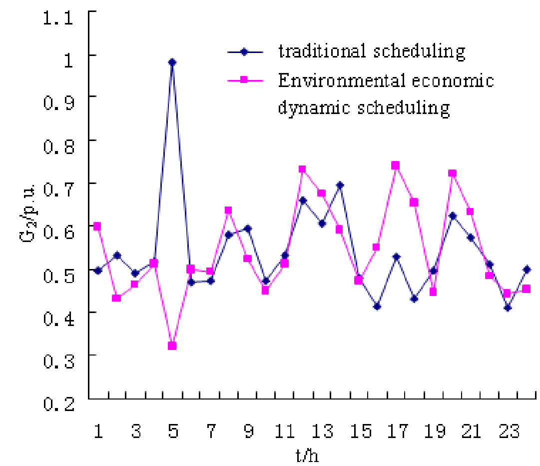


Fig. 3: The daily output curve of unit 2 under the two methods of scheduling.

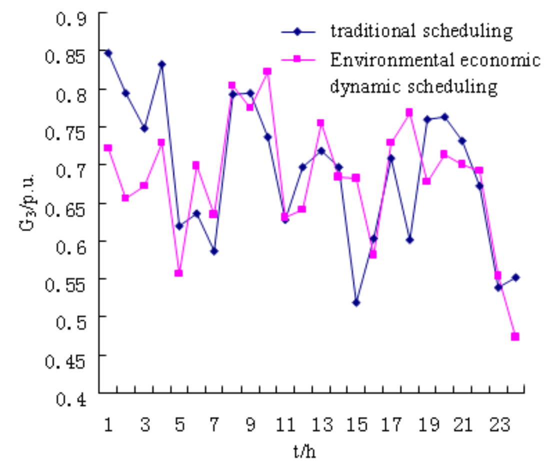


Fig. 4: The daily output curve of unit 3 under the two methods of scheduling.

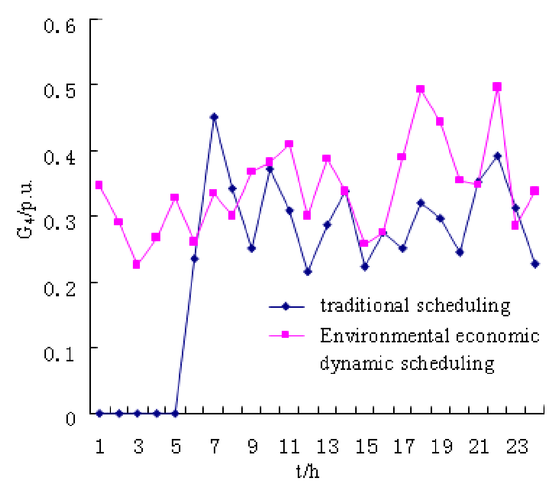


Fig. 5: The daily output curve of unit 4 under the two methods of scheduling.

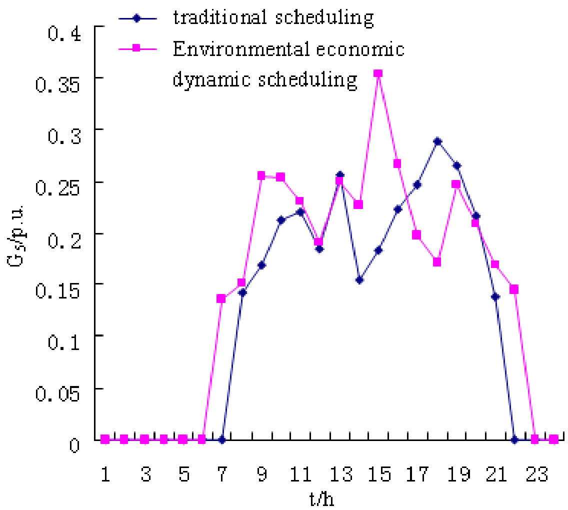


Fig. 6: The daily output curve of unit 5 under the two methods of scheduling.

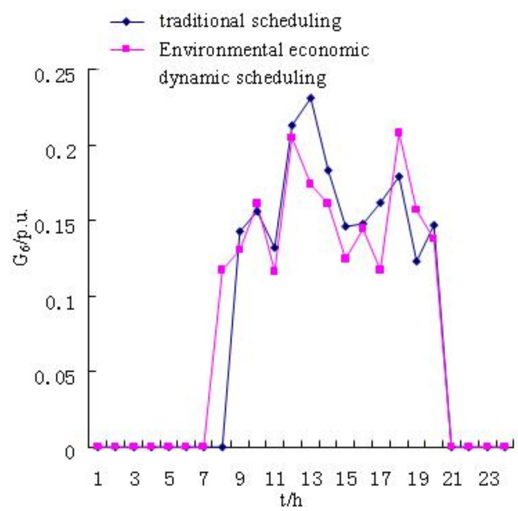


Fig. 7: The daily output curve of unit 6 under the two methods of scheduling.

Table 4: Fuel characteristics of conventional generators.

| Unit | $E^i_{CO2}$ | $q^i_a$ (MJ/kg) |
|---|---|---|
| 1 | 23.9332 | 25.8627 |
| 2 | 38.9529 | 14.8726 |
| 3 | 34.2126 | 13.0714 |
| 4 | 40.5933 | 12.2880 |
| 5 | 42.0152 | 11.1917 |
| 6 | 44.1282 | 10.5303 |

but it is prone to premature. Simulated annealing algorithm can converge to the global optimum in greater probability, but its convergence speed is slow, and there are many constraints. This article combines organically the advantages of PSO and SA to make the PSO algorithm escape from the local extreme points in a larger probability, at the same time, it improves the SA algorithm convergence speed. PSO and SA algorithm are compared with the traditional particle swarm optimization (PSO) algorithm, the calculation speed and calculation accuracy and so on, all have certain advancement.

The calculation process of PSO-SA algorithm is shown in Fig. 1.

## CASE ANALYSIS

To validate the proposed environmental economic dynamic dispatch modelling including wind farms, the testing system which contains 1 wind farm and 6 sets of thermal power units is simulated in this paper; the scheduling period is 1 d and divided into 24 hours. The algorithm of population size takes 20; maximum iterations number takes 200; learning factor $C_1 = C_2 = 2.0$; initial temperature takes 100; terminate temperature takes 50; annealing coefficient $\alpha$ takes 0.95. Set No. 1 generator is balance unit, power base value takes 100 mV A. System daily load data are shown in Table 2, wind power prediction data are shown in Table 3, the thermal power unit with the fuel characteristics and thermal power unit parameters, respectively, are shown in Tables 4 and 5.

The system forecast wind farm output value is small, while, in order to respond positively to the "Renewable Energy Law" for wind power and other renewable energy policies to support full access, we use wind power priority access to the internet in full operating mode.

Figs. 2-7 are the unit $G_1$-$G_6$ the open stands and the load distribution case under the two methods of environmental economic dynamic scheduling and traditional scheduling.

Table 6 is the two cases of conventional generators resource consumption contrast under the optimizing dispatching considered energy environmental benefits before and after. From the data in Table 6, it can be seen that when environmental economic dynamic dispatch modelling was used to dispatch, routine resource consumption of the unit increased from 129307.8345 $ to 131986.4362$ and power generation resource consumption rose by 2678.6017$. However, compared with traditional scheduling, energy environmental benefits rose by 0.6208$.

Through the analysis of Figs. 2-7 and Table 6, it can be obtained, considering the energy and environment benefits, which will slightly improve thermal power unit resources consumption, but at the same time, greatly increasing the environmental benefits of energy source for the whole power system, this "invisible capital", and reduce the pollution and destruction of ecological environment. Thus, developing low

Table 5: Conventional generators' parameters.

| Unit | $P_i^{max}$/pu | $P_i^{min}$/pu | $a_i$/(\$/h) | $b_i$/(\$/MW.h | $c_i$/(\$/MW.h | $d_i$/\$ | $s_i$/\$ | $t_i$/h | $T_{imin}^{on}$/h | $T_{imin}^{off}$/h | $r_i^{up}$/(pu/h) | $r_i^{down}$/(pu/h) | $h_{ie}$ | $a_{i/(MW)}$ | $b_{i/(MW)-1}$ | $g_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4 | 1.2 | 663.3562 | 36.1938 | 0.2048 | 4500 | 4500 | 4 | 8 | 8 | 0.8 | -0.8 | 0.75 | -0.03 | 0.1375 | 0.83 |
| 2 | 1.3 | 0.2 | 932.6582 | 45.6024 | 0.1332 | 550 | 550 | 2 | 5 | 5 | 0.3 | -0.3 | 0.5 | -0.25 | 0.4017 | 0.7466 |
| 3 | 1.3 | 0.2 | 876.7851 | 42.5818 | 0.1298 | 560 | 560 | 2 | 5 | 5 | 0.3 | -0.3 | 0.55 | -0.19 | 0.3775 | 0.7795 |
| 4 | 0.8 | 0.2 | 1235.2237 | 38.2607 | 0.064 | 170 | 170 | 2 | 3 | 3 | 0.25 | -0.25 | 0.4 | -0.12 | 0.3228 | 0.7496 |
| 5 | 0.6 | 0.1 | 1332.3704 | 39.9277 | 0.0254 | 30 | 30 | 1 | 1 | 1 | 0.15 | -0.15 | 0.35 | -0.75 | 0.5301 | 0.7472 |
| 6 | 0.5 | 0.1 | 1658.1029 | 35.2756 | 0.0128 | 30 | 30 | 1 | 1 | 1 | 0.15 | -0.15 | 0.3 | -0.67 | 0.4866 | 0.752 |

Table 6: Environmental economic dynamic scheduling and traditional scheduling target value comparison.

| Objective | Traditional scheduling | Environmental and economic dynamic scheduling |
|---|---|---|
| Resource Consumption/$ | 129307.8345 | 131986.4362 |
| Energy Environmental Benefits/$ | 11.4518 | 12.0726 |

carbon economy, countries around the world under the background of the implementation of energy conservation and emissions reduction, energy and environment benefits for optimizing power system scheduling is more far-reaching significance.

## CONCLUSIONS

Based on the optimal dispatch in traditional power system, the concept of "energy-environmental efficiency" was introduced to modify the optimal dispatch model in wind power integrated system, and the multi-objective optimal dispatch model was proposed on the basis of comprehensively considering the minimum of the resource consumption, the best energy-environmental efficiency and the highest system stability. Energy and environment efficiency model is established from the perspective of ecological environment; the key is to study the effect of electric power production to ecological environment. The model has produced more positive influence for the current power system scheduling in the strategic policy of vigorously developing the wind power to reduce environmental pollution. In this paper, the maximum fuzzy satisfaction degree method and the improved particle swarm combined with simulated annealing thought are adopted to calculate and to gain a higher quality solutions. Example validation, scheduling model constructed in this paper is reasonable, the resulting electricity production scheduling scheme could meet economic requirements, at the same time, and it has a certain practicality for promoting "low carbon" of electric power production.

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