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A MULTI-SUBPOPULATION BAT OPTIMIZATION ALGORITHM FOR ECONOMIC DISPATCH PROBLEM WITH NON-ESSENTIAL DEMAND RESPONSE

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In this paper, we propose a new economic dispatch model with random wind power, demand response and carbon tax. The specific feature of the demand response model is that the consumer's electricity demand is divided into two parts: necessary part and non-essential part. The part of the consumer's participation in the demand response is the non-essential part of the electricity consumption. The optimal dispatch objective is to obtain the minimum total cost (fuel cost, random wind power cost and emission cost) and the maximum consumer's non-essential demand response benefit while satisfying some given constraints. In order to solve the optimal dispatch objective, a multi-subpopulation bat optimization algorithm (MSPBA) is proposed by using different search strategies. Finally, a case of an economic dispatch model is given to verify the feasibility and effectiveness of the established mathematical model and proposed algorithm. The economic dispatch model includes three thermal generators, two wind turbines and two consumers. The simulation results show that the proposed model can reduce the consumer's electricity demand, reduce fuel cost and reduce the impact on the environment while considering random wind energy, non-essential demand response and carbon tax. In addition, the superiority of the proposed algorithm is verified by comparing with the optimization results of CPLEX+YALMIP toolbox for MATLAB, BA, DBA and ILSSIWBA.

Keywords: economic dispatch, non-essential demand response, random wind power, bat algorithm, multi-subpopulation

Classification: 90Bxx

1. INTRODUCTION

Economic dispatch is an important problem in power system optimization dispatch. Its purpose is to minimize the fuel cost after power generation while satisfying some equality and inequality constraints. However, environmental problems caused by fossil fuel during power generation are intensifying in traditional economic dispatch. Thus, it is necessary to propose a better solution by combining both the objectives of cost and emission. With the integration of multiple forms of renewable energy into the power system, environmental challenges are largely alleviated. Wind energy, a common form of renewable energy, has been applied to economic dispatch problem in power system.

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For example, a novel hybrid bat algorithm was proposed to deal with the economic dispatch problem incorporating thermal generators and wind turbines in [24]. In [15], a distributed economic dispatch method was proposed, which combines traditional thermal generators and wind turbines. The aggregated virtual power plants was used for a two-phase economic dispatch model incorporating wind turbines [23]. In [39], a computation framework for power system daily operations considering wind power uncertainties was proposed, which included two major stages, wind power forecast and stochastic unit commitment/economic dispatch.

Nowadays, most optimization problems are complex problems of highly nonlinear and multi-constrained, especially dispatch problem in power systems. The objective of optimization problems is usually the minimum cost, the least impact on the environment, the maximum utilization, the biggest profit and so on [26]. Traditional methods, such as linear programming [18], dynamic programming [4], λ-iteration method [34], gradient method [22], projection method [14] and other methods often fail to solve such large-scale problems, especially nonlinear objective functions. Most of them require use of gradient information to solve non-differentiable functions. In addition, such techniques often fail to solve optimization problems with many local optimal solutions. Therefore, many intelligent algorithms have been proposed to solve such optimization problems and have obtained good effectiveness. These intelligent algorithms include genetic algorithm (GA) [3, 38], differential evolution (DE) [6], particle swarm optimization (PSO) [21, 30], cuckoo search (CS) [36], ant colony optimization (ACO) [7], etc. With the deepening of intelligent algorithm research, it is more and more widely used in signal processing, automatic control, optimization dispatch, pattern recognition and so on.

BA is a swarm intelligence algorithm proposed by Professor Yang in 2010, inspired by the behavior of bat hunting for prey [35]. Some previous studies have shown that BA has better efficiency and stability when solving engineering optimization problems [12, 37]. However, BA has some shortcomings including easy to fall into local optima and low precision of solution when solving some complex problem. In order to solve high dimensional, highly nonlinear complex optimization problem, some improved versions of BA have been proposed. In [11], the chaotic mapping was introduced into BA to improve the global search ability. The simulated annealing and Gaussian perturbation was combined with BA to improve global convergence speed and accuracy [16]. The directional echolocation was introduced in BA to enhance its exploration and exploitation capabilities [2]. In addition, There are also different versions of BA that have been applied to economic/emission dispatch problem, control system parameter optimization, etc.

Recently, many intelligent meta heuristic algorithms have been proposed to solve the economic dispatch problem. For example, a modified gravitational search algorithm based on a non-dominated sorting genetic approach was proposed for hydro-thermal-wind economic emission dispatch problem in [5]. A modified harmony search algorithm was proposed for environmental/economic dispatch [19]. In [32], a hybrid ACO-ABC-HS optimization algorithm was used for economic dispatch problem. An implementation of flower pollination algorithm was applied to solve economic load dispatch and combined economic emission dispatch problems [1].

In the above literature, the economic/emission dispatch models are based on the power generation side. With the continuous development of power industry, relying solely on dispatching power generation resources has not been able to meet the energy and power shortages. The demand side response changes the "one-way" mode of resource planning in the traditional dispatch mode by relying only on the power generation side resources, and the dispatch mode performs a "two-way" interactive transition of the integrated resource allocation to the power generation side and the user side. At present, the flexible interactive intelligent power consumption method that considers the demand side response has become a research focus and development trend [29].

In this paper, we present an economic dispatch model incorporating random wind power, non-essential demand response and carbon tax, which objective is the minimum fuel cost of traditional thermal generators, the minimum cost of wind power and the maximum consumer's non-essential demand response benefit. At the same time, the proposed model must satisfy some equality and inequality constraints. The proposed demand response model is to let consumers participate in the process of power distribution and reduces the electricity demand by giving proper compensation to customers. The demand response model proposed is characterized by dividing the consumer's demand for electricity into essential and non-essential parts. That is, the consumer must partially use the electricity consumption, and the consumer's reduced electricity consumption is the non-essential part of the electricity consumption. In the case of considering the power company to obtain a certain profit, the objective of the demand response is the the maximum benefit of the consumers. Moreover, we propose a multi-subpopulation bat optimization algorithm (MSPBA). The main idea is to divide the population into three subgroups by using three different search strategies. The first subgroup does global search to improve the global exploration ability of the algorithm. The second subgroup performs local search to improve the accuracy of the algorithm. The third subgroup is used to jump out of the local optima. At last, the validity and feasibility of the proposed algorithm and model are verified by numerical simulations. It is also shown that the proposed model can reduce the consumer's electricity demand, reduce fuel cost and reduce the impact on the environment while considering random wind energy, non-essential demand response and carbon tax.

The other sections of this paper are arranged as follows: The model of economic dispatch with non-essential demand response is described in section 2. The multi-subpopulation strategy based bat algorithm is presented in section 3. Then, the results of numerical experiments based on the proposed model and algorithm are presented in section 4. The conclusion is described in Section 5.

2. PROBLEM FORMULATION

The present formulation treats economic dispatch problem of non-essential demand response and carbon tax which attempts to minimize the total cost, while satisfying some equality and inequality constraints. The total cost include three parts: thermal generators (TGs) cost, wind turbines cost and emission cost. The objectives and constraints of economic dispatch problem are formulated as follows.

2.1. The total cost objective function

2.1.1. The cost function of thermal generators and random wind turbines

The cost function of thermal generators and wind turbines is expressed as [17]:

$$S_1 = \sum_{n=1}^{N_s}\sum_{t=1}^{T} f_n(P_{n,t}) + \sum_{r=1}^{N_r}\sum_{t=1}^{T} g_r(W_{r,t}) \tag{1}$$

where N_s , N_r are the numbers of TGs and WTs, respectively, P_n, W_r are the scheduled power outputs of the nth TG and the rth WT, respectively.

1) The fuel cost function of each thermal generating unit considering valve-point effects [33] is expressed as:

$$f_n(P_{n,t}) = a_n P_{n,t}^2 + b_n P_{n,t} + c_n + |d_n \sin(e_n(P_n^{\min} - P_{n,t}))| \tag{2}$$

where a_n, b_n, c_n, d_n and e_n are the cost coefficients of the nth TG.

2) The cost of jth WT is described as [17, 25]:

$$g_r(W_{r,t}) = d_r W_{r,t} + C_{ow,r}E(Y_{oe,r,t}) + C_{uw,r}E(Y_{ue,r,t}) \tag{3}$$

where $d_r W_r$ is a linear cost function for wind power generation with d_r being the cost coefficient or the "price" of the rth WT; $C_{ow,r}$ represents the cost coefficient of purchasing electricity from other sources due to overestimation of the availability of rth wind power, and $C_{uw,r}$ indicates that the cost coefficient of all wind power provided by the wind turbine is fully utilized due to underestimation of the availability of rth wind power; $C_{uw,r}E(Y_{ue,r,t})$ and $C_{ow,r}E(Y_{oe,r,t})$ denote the costs of underestimation $Y_{ue}(= W_r - W_{predict})$ and overestimation $Y_{oe}(= W_{predict} - W_r)$ for the rth wind turbine, respectively; $E(Y_{ue,r,t})$ and $E(Y_{oe,r,t})$ represent the average of the underestimation and overestimation of wind energy, respectively. The definitions of $E(Y_{ue,r,t})$ and $E(Y_{oe,r,t})$ are more complicated and not given because of space limitation. Their detailed introduction are referred to [2].

2.1.2. Emission cost function (carbon tax)

The amount of emissions caused by fossil-fueled generating units such as carbon dioxide (CO_2), nitrogen oxides (NO_x) and sulphur oxides (SO_x) are modelled as a sum of quadratic and exponential terms in the emission function. The mathematical formulation of the emission function is given by [13]:

$$E(P_{n,t}) = \sum_{t=1}^{T}\sum_{n=1}^{N_s}[10^{-2}(\alpha_n P_{n,t}^2 + \beta_n P_{n,t} + \gamma_n) + \varepsilon_n \exp(\lambda_n P_{n,t})] \tag{4}$$

where $\alpha_n, \beta_n, \gamma_n, \varepsilon_n$ and λ_n are emission coefficients of the nth TG.

Recently, environmental problems caused by fuel combustion have intensified, and many countries impose a carbon tax on greenhouse gas emissions to reduce carbon emissions. The purpose is to encourage investment in clean energy such as wind energy. The emission cost function is represented as:

$$f_2 = C_{tax} C_{ef} E(P_{n,t}) \tag{5}$$

where C_{tax} is the carbon tax price of the unit of the thermal generator, and C_{ef} is the fuel emission factor of CO_2 for thermal generator.

In summary, the total minimum cost function is expressed as:

$$\min \quad F_1 = S_1 + f_2. \tag{6}$$

2.2. Constraint conditions

In economic dispatch problem, the objective functions are subjected to the following equality and inequality constraints.

2.2.1. Power balance constraint

The power balance constraint is described as:

$$\sum_{n=1}^{N_s} P_{n,t} + \sum_{r=1}^{N_r} W_{r,t} = P_d^t + P_{loss}^t \tag{7}$$

where $t \in (1, 2, \ldots, T)$, P_d^t and P_{loss}^t are the power load demand and transmission losses at the t time interval, respectively. P_{loss}^t can be represented by B-loss coefficients, which is calculated by

$$P_{loss}^t = \sum_{n=1}^{N_s} \sum_{i=1}^{N_s} P_{n,t} B_{n,i} P_{i,t} + \sum_{n=1}^{N_s} B_{0,n} P_{n,t} + B_{oo} \tag{8}$$

where $B_{n,i}$, $B_{0,n}$ and B_{oo} are the power transmission loss B coefficient matrix.

2.2.2. Generation power limits

The active power output limit for the nth TG and the rth WT are given by

$$P_n^{\min} \leqslant P_{n,t} \leqslant P_n^{\max} \tag{9}$$

$$W_r^{\min} \leqslant W_{r,t} \leqslant W_r^{\max} \tag{10}$$

where $P_n^{\min}$ and $P_n^{\max}$ are the lower and upper bounds of active power output for the nth TG, respectively; $W_r^{\min}$ and $W_r^{\max}$ are the lower and upper bounds of active power output for the rth WT, respectively.

2.2.3. Ramp rate limits

The ramp rate characteristic of thermal generators can be expressed as:

$$P_{n,t} - P_{n,t-1} \leqslant UR_n \tag{11}$$

$$P_{n,t-1} - P_{n,t} \leqslant DR_n \tag{12}$$

where UR_n and DR_n denote the up and down ramp rate limit of nth TG.

2.3. Non-essential demand response model

Demand response is a measure of consumers participating in the process of power distribution. The purpose is to adopt a certain compensation strategy to enable consumers to reduce the need for electrical energy within a reasonable range. Inspired by [29], this paper proposes a demand response model based on consumer benefits. Firstly, let $P_{(B)j,t}$ and $p_{(n)j,t}$ denote the necessary part and non-essential part of the power demand of the j-consumer during the t time interval, respectively. When the j-consumer does not participate in the demand response in the t time interval, the total power demand is given by:

$$P_{(D)j,t} = P_{(B)j,t} + p_{(n)j,t}. \tag{13}$$

After the consumer participates in the demand response, the reduced power consumption is the non-essential part of the power demand $p_{(n)j,t}$. When the consumer participates in the demand response, the total power demand of the j-consumer during the t time interval is described as:

$$P_{(C)j,t} = P_{(B)j,t} + q_{j,t} \tag{14}$$

where $q_{j,t}$ indicates the actual power consumption of the non-essential part of the j-consumer after participating in the demand response during the t time interval. Therefore, the reduction in power consumption of consumers is calculated by:

$$m_{j,t} = p_{(n)j,t} - q_{j,t}. \tag{15}$$

$L_{j,t}(m, \theta)$ is defined as the loss of j-consumer's use of m MW during the t time interval. The consumer benefit can be expressed as:

$$y_{j,t}(m, \theta) = \beta_t m_{j,t} - L_{j,t}(m, \theta) \tag{16}$$

where β_t is the compensation for the power company to reduce the amount of power per MW for consumers during the t time interval. θ is the participation factor [9, 27, 28], $\theta \in [0, 1]$, the larger θ, the higher participation enthusiasm of consumers. In this paper, the mathematical function of $L_{j,t}(m, \theta)$ is defined as follow [8]:

$$L_{j,t}(m, \theta) = k_1 m_{j,t}^2 + k_2 m_{j,t} - k_2 m_{j,t} \theta_j \tag{17}$$

where k_1, k_2 are the loss coefficients. Similarly, the profits of the power company are expressed as:

$$C_{j,t} = (\lambda_t - \beta_t) m_{j,t} \tag{18}$$

where λ_t is the cost reduced by the power company for each MW reduction in power supply during the t time interval.

We take the maximum consumer interest as the objective function, which is given by:

$$\max \quad F_2 = \sum_{t=1}^{T} \sum_{j=1}^{J} [\beta_t m_{j,t} - L_{j,t}(m, \theta)] \tag{19}$$

s.t.

$$\sum_{t=1}^{T} \lambda_t m_{j,t} > \sum_{t=1}^{T} \beta_t m_{j,t}, j = 1, \ldots, J \tag{20}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} \beta_t m_{j,t} \leqslant UB \tag{21}$$

$$0 \leqslant m_{j,t} \leqslant p_{(n)j,t} \tag{22}$$

$$\sum_{t=1}^{T} m_{j,t} \leqslant CM_j \tag{23}$$

where UB is the budget compensation limit of the power company and CM_j is the upper limit of the j-consumer's ability to reduce power consumption during the T scheduling period. The constraint (20) indicates that the cost of reducing power consumption by consumers is greater than the compensation of the power company in each time interval. That is, the profit of power companies is greater than that of consumers who do not participate in demand response. The constraint (21) ensures that the total compensation cost is less than the budget ceiling of the power company. The constraint (22) ensures that the power consumption reduced by each consumer is between 0 and $p_{(n)j,t}$ at each t time interval. The constraint (23) ensures the total power consumption by each customer is less than the upper limit of interruptible power.

Remark 2.1. The demand response in literature [29] only considers the consumer's power consumption reduction and its corresponding compensation, and does not consider the range of consumers' reduced power consumption. Its objective is the maximum benefit of the power company. In this paper, the demand response considers that the consumer must partially use the electricity consumption, and the consumer's reduced electricity consumption is the non-essential part of the electricity consumption. In the case of considering the power company to obtain a certain profit, the objective of the demand response is to maximize benefit of the consumers. That is, the more compensation the consumer receives, the higher the enthusiasm for participating in the demand response, and the more power is reduced.

2.4. The economic dispatch with non-essential demand response and carbon tax

In this section, the economic dispatch with non-essential demand response and carbon tax is proposed. Its specific advantage is to take into account two aspects of the power generation side and the demand side, so that consumers participate in the process of power distribution. Under the certain incentives of the power company, taking into account the profit of the power company and the benefits of the consumers, the power demand of the consumers is appropriately reduced, thereby reducing the burden on the power generation side.

For the economic dispatch with demand response and carbon tax, there are two objective functions. The first objective function is to minimize total costs (including thermal generator, wind turbine and emission cost). The second objective function is to maximize the consumer's benefit under the demand response. The mathematical form of the total objective function is as follows:

$$\min\ F = \omega_1 \left[\sum_{n=1}^{N_s} \sum_{t=1}^{T} f_n(P_{n,t}) + \sum_{r=1}^{N_r} \sum_{t=1}^{T} g_r(W_{r,t}) + \sum_{n=1}^{N_s} \sum_{t=1}^{T} C_{tax} C_{ef} E(P_{n,t}) \right] + (1-\omega_1) \sum_{t=1}^{T} \sum_{j=1}^{J} [L_{j,t}(m,\theta) - \beta_t m_{j,t}]. \tag{24}$$

A simplified form of the total objective function can be expressed as:

$$\min\ F = \omega_1 F_1 + (1-\omega_1)(-F_2) \tag{25}$$

where ω_1 and $1-\omega_1$ are the objective function weights. Since the objective function F_2 is maximization value, the negative value of F_2 in the total objective function F is to minimized. The constraints of the total objective function are not changed except the power balance constraint (7). It is modified as below:

$$\sum_{n=1}^{N_s} P_{n,t} + \sum_{r=1}^{N_r} W_{r,t} = \sum_{j=1}^{J} P_{(B)j,t} + \sum_{j=1}^{J} q_{j,t} + P_{loss}^t. \tag{26}$$

In summary, the constraints of the total objective function (24) are as follows:

$$\sum_{n=1}^{N_s} P_{n,t} + \sum_{r=1}^{N_r} W_{r,t} = \sum_{j=1}^{J} P_{(B)j,t} + \sum_{j=1}^{J} q_{j,t} + P_{loss}^t \tag{27}$$

$$P_{loss}^t = \sum_{n=1}^{N_s} \sum_{i=1}^{N_s} P_{n,t} B_{n,i} P_{i,t} + \sum_{n=1}^{N_s} B_{0,n} P_{n,t} + B_{oo} \tag{28}$$

$$P_n^{\min} \leqslant P_{n,t} \leqslant P_n^{\max} \tag{29}$$

$$W_r^{\min} \leqslant W_{r,t} \leqslant W_r^{\max} \tag{30}$$

$$P_{n,t} - P_{n,t-1} \leqslant UR_n \tag{31}$$

$$P_{n,t-1} - P_{n,t} \leqslant DR_n \tag{32}$$

$$\sum_{t=1}^{T} \lambda_t m_{j,t} > \sum_{t=1}^{T} \beta_t m_{j,t},\ j = 1, \ldots, J \tag{33}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} \beta_t m_{j,t} \leqslant UB \tag{34}$$

$$0 \leqslant m_{j,t} \leqslant p_{(n)j,t} \tag{35}$$

$$\sum_{t=1}^{T} m_{j,t} \leqslant CM_j. \tag{36}$$

3. MULTI-SUBPOPULATION BAT ALGORITHM (MSPBA)

In this section, the main idea and steps of BA are described. In view of the shortcoming of the BA, which tends to fall into local optima and low accuracy of solution, multi-subpopulation bat algorithm (MSPBA) is proposed. The main idea of MSPBA is that the total population of bats is divided into three subpopulation according to the initial fitness value. The first and second subpopulation are mainly used for global and local search with the aim to enhance the exploitation and exploration capabilities, the third subpopulation strategy is used to escape local optima.

3.1. The bat algorithm

Tiny bats use a sonar called echo locator to detect prey and avoid obstacles. They usually emit a very loud sound pulse and can hear the sound reflected back from around the object. When searching for prey, the ratio of pulses emitted by bats flying close to prey can quickly reach a large value. However, the direction of the sound pulse decreases when bats gradually approach the prey. Based on the above behavior, BA was proposed by professor Yang (2010) [35]. For simplicity, Yang(2010) formulated the following approximate or idealized rules [35]:

1) All bats use echolocation to sense distance, and they also "know" the difference between food/prey and background barriers in some magical way [35];

2) Bats fly randomly with velocity v_i at position x_i with a fixed frequency $f_{\min}$, varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0, 1]$, depending on the proximity of their target [35];

3) Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value $A_{\min}$ [35].

For each virtual bat, its position (x_i) and velocity (v_i) in a d-dimensional search space should be defined. x_i and v_i should be subsequently updated during the iterations. The pulse frequency f_i, velocity v_i^t and solution x_i^t at time step t are defined by:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta_o \tag{37}$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*^t) f_i \tag{38}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{39}$$

where $\beta_o \sim U([0,1])$ is a uniformly distributed random number; $f_{\max}$ and $f_{\min}$ are the maximum and minimum pulse frequency; x_*^t is the current global best location (solution) at time step t in the current population.

For the local search part, a new solution for each bat is generated locally using random walk given by:

$$x_{i,new}^{t+1} = x_*^t + \xi A^t \tag{40}$$

where $\xi \sim U([0,1])$ is a random number, and A^t is the average loudness at time step t.

The loudness A_i and the rate of pulses emission r_i are updated as the iterations proceed. The loudness decreases and the pulse rate increases as the bat gets closer to its prey. The loudness and the pulse rate are described as follow:

$$A_i^{t+1} = \alpha_m A_i^t \tag{41}$$

$$r_i^{t+1} = r_i^0 (1 - \exp(-\gamma_m t)) \tag{42}$$

where $0 < \alpha_m < 1$ and $\gamma_m > 0$ are constants. As $t \to \infty$, we have $A_i^t \to 0$ and $r_i^t \to r_i^0$. The initial loudness A_0 can typically be $A_0 \sim U([1, 2])$, while the initial emission rate $r_0 \sim U([0, 1])$. The pseudo code of BA is shown in Algorithm 1.

Algorithm 1: The bat algorithm (BA)

1. Define the objective function $f(x)$, $x = (x_1, x_2, \ldots, x_n)^T$
2. Initialize the bat population x_i, v_i, A_i, $f_{\min}$, $f_{\max}$ and r_i
3. Get the fitness value and the current best solution by Initialize population
4. **While**($t <$ Max number of iterations)
5. Update f_i, v_i and x_i by the equations (37), (38) and (39)
6. **if** ($rand > r_i$)
7. Select a solution among the best solutions
8. Generate a local solution by the equation (40)
9. **end if**
10. **if** ($rand < A_i$ & $f(x_i) < f(x_*)$)
11. Accept the new solutions
12. Update r_i and A_i by the equations (41), (42)
13. **end if**
14. Rank the bats and find the current best x_*
15. **end while**
16. Postprocess results and visualization

3.2. The first subpopulation search model

The first subpopulation is mainly used for global search with the aim to enhance the exploitation capability. So the pulse rate of bat (r_i) should be set to a larger value between 0 and 1 ($r_i = 0.8$). A small number of bats conduct basic local search according to (40). The frequency of bats is produced by the Cauchy distribution, and each dimension of bats searches at different velocities. The current best location x_*^t is replaced by a random solution x_k^t to expand the global search capability. The bat population is one-third of the entire population. The mathematical formulas of the bats' movement are as follows:

$$f_i = 0.1 \cdot \tan(\pi \cdot (\epsilon - 1/2)) \tag{43}$$

$$v_i^{t+1} = (x_j^t - x_k^t) f_i \tag{44}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{45}$$

where ϵ is a uniformly distributed random number, $\epsilon \sim U([0, 1])$.

3.3. The second subpopulation search model

The second subpopulation is concerned about the local search mode. A new local search mechanism is used to enhance the exploration capability of the algorithm. In the local search process of BA, (40) only shows that the bats are allowed to move from their current positions to new random positions and not toward the optimal individual. Therefore the local search of BA is less effective and the result is not very accurate. In order to overcome these weakness, the new local search update formula is given by:

$$x_i^{t+1} = x_i^t + \alpha(x_*^t - x_i^t) + \beta(x_j^t - x_k^t), \quad (t = 1) \tag{46}$$

$$x_i^{t+1} = x_i^t + c(x_j^t - x_k^t) + W, \quad (t \neq 1) \tag{47}$$

$$W = \gamma \cdot a(x_*^t - x_i^t) + (1-\gamma) \cdot b(x_*^{t-1} - x_i^t) \tag{48}$$

where x_*^t, x_*^{t-1} are the best solutions at iteration step t and $t-1$ in the current population, respectively. γ is a weight coefficient, which represents the proportion of learning from the best solutions at iteration step t and $t-1$. α, β, a and b are random numbers between 0 and 1.

The second subpopulation selects a few number of individuals for global search, which avoids excessive concentration of the subpopulation for local search. The pulse frequency of global search is generated by the Lévy flight [31], and then the update formula of the speed and solution of the each bat is obtained. Their specific mathematical forms are expressed by:

$$f_i = L(\lambda) \tag{49}$$

$$v_i^{t+1} = \mu(x_i^t - x_*^t)f_i \tag{50}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{51}$$

where μ is the pulse frequency scaling factor, $L(\lambda)$ is a function that follows the Lévy distribution, and $L(\lambda)$ can be expressed by:

$$L(\lambda) \sim \frac{\lambda \Gamma(\lambda) \sin(\frac{\lambda\pi}{2})}{\pi} \frac{1}{s^{1+\lambda}} \quad (s \gg s_0 > 0) \tag{52}$$

where $\lambda = \frac{3}{2}$, $\Gamma(\lambda)$ is the standard gamma function.

3.4. The third subpopulation search model

In order to enhance the diversity of the population and escape local optima, the third subpopulation generates random individuals through logical chaotic mapping, and retains the optimal solution.

A logistic chaotic mapping system [20] can be produced using the following expression:

$$x^{t+1} = ux^t(1 - x^t) \tag{53}$$

where t represents the step of iterations and u is the chaos control parameter. If $u = 4$, then the above defined system exhibits chaotic behavior. The chaotic variable Cx_i expression is as follows:

$$Cx_i^{t+1} = 4Cx_i^t(1 - Cx_i^t) \tag{54}$$

$$Cx_i = (x_i - Lb_i)/(Ub_i - Lb_i) \tag{55}$$

$$x_i' = Lb_i + Cx_i(Ub_i - Lb_i) \tag{56}$$

where x_i is mapped to a chaotic variable Cx_i between 0 and 1 according to (55). $x_i \in [Lb_i, Ub_i]$ in (54) can be changed into Cx_i using expressions (55) and (56), where x_i' means to transform chaotic variable Cx_i into traditional variable after the chaotic mapping transformation.

When $Cx_i \sim U([0,1])$ and $Cx_i \notin \{0.25, 0.50, 0.75\}$, the subpopulation will be in a chaotic state. The pseudo code of MSPBA is shown in Algorithm 2.

Algorithm 2: The Multi-subpopulation bat algorithm (MSPBA)

1. Define the objective function $f(x)$, $x = (x_1, x_2, \dots, x_n)^T$
2. Initialize the bat population x_i, v_i, A_i, $f_{\min}$, $f_{\max}$ and r_i
3. Get the fitness value and the current best solution by Initialize population
4. **While** (t <Max number of iterations)
5. Divide the population into three subgroups according to fitness values ($n/3$)
6. **for** $i = 1 : n/3$
7. (1) Update f_i, v_i and x_i by the equations (43), (44) and (45)
8. **if** ($rand > r_i$)
9. Generate a local solution by the equation (40)
10. **if** ($rand < A_i$ & $f(x_i) < f(x_*)$)
11. Accept the new solutions
12. **end if**
13. (2) Update f_i, v_i and x_i by the equations (46), (47) and (48)
14. **if** ($rand > r_i$)
15. Generate a local solution by the equations (49), (50) and (51)
16. **if** ($rand < A_i$ & $f(x_i) < f(x_*)$)
17. Accept the new solutions
18. **end if**
19. (3) Generate g random each bats through chaotic sequences by the equations (53)-(56), retaining the best each bats
21. **if** ($rand < A_i$ & $f(x_i) < f(x_*)$)
22. Accept the new solutions
23. Update r_i and A_i by the equations (41), (42)
24. **end if**
25. Rank the three subpopulation bats and find the current best x_*
26. **end while**
27. Postprocess results and visualization

4. EXPERIMENT AND DISCUSSION

In order to validate the superiority of the proposed MSPBA, we perform two different forms of simulation experiment. The first one is to use MSPBA to solve a case of economic dispatch that considers demand response. This economic dispatch model includes three thermal generators, two wind turbines and two consumers. The second one is compared with other four methods based on this economic dispatch model. Experiment environment: MATLAB2012a; Win 7; Intel Core i5-4690 CPU; 3.3GHz; 4GB RAM.

4.1. Simulation results and analysis for a case using MSPBA

In order to verify the feasibility of the proposed model and algorithm, we select a case including three thermal generators, two wind turbines and two consumers. The scheduling period is 24 hours. The decision variables are $P_{n,t}$, $W_{r,t}$ and $m_{j,t}$. The population n, loudnessA_i and pulse emission rate r_i are set as 180, 0.5 and 0.8, respectively. The frequency f_i is produced by the Cauchy distribution. Table 1 shows thermal generator fuel cost parameters. Table 2 shows thermal generator emission parameters and ramp rate limits and Table 3 shows wind turbine parameters. The carbon tax C_{tax} and emission factor C_{ef} are set to USD20\$/t, 3.1604kg/kg. Two wind turbine parameters and wind power predictions are taken from [39]. The total hourly necessary partial power demand $P^t_{(B)}$, the total hourly non-essential partial power demand $P^t_{(n)}$, the cost of per MW for the t time interval λ_t and the power company's compensation of per MW for the t time interval β_t are shown in Table 4. Table 5 shows the customer participation factor (θ_j), the customer loss coefficient($k_{1,j}$ and $k_{2,j}$) and the consumer upper limit of interruptible power in 24 hour(CM_j). The budget compensation limit of the power company (UB) is \$ 50000.

n	a_n(\$/$(MW)^2h$)	b_n(\$/MWh)	c_n(\$/h)	d_n(\$/h)	e_n(1/MW)	$P_n^{\min}$	$P_n^{\max}$
1	0.002	10	200	200	0.08	20	110
2	0.0025	15	250	300	0.04	20	100
3	0.0018	19	600	400	0.04	120	600

Tab. 1. Thermal generator fuel cost parameters.

n	α_n	β_n	γ_n	ε_n	λ_n	UR_n(MW/h)	DR_n(MW/h)
1	0.00004	0.2	40	0.4968	0.01925	20	60
2	0.00005	0.3	50	0.4860	0.01694	20	60
3	0.000024	0.12	80	0.5035	0.01478	120	160

Tab. 2. Thermal generator emission parameters and ramp rate limits.

r	d_r	$C_{ow,r}$	$C_{uw,r}$	v_{in}	v_{out}	v_r	w_r	C	k
1	0	30	5	4	25	16	3	4.6024	1.8862
2	0	20	5	3	25	13	3	4.4363	1.7128

Tab. 3. Wind turbine parameters.

Time(h)	$P^t_{(B)}$(MW)	$P^t_{(n)}$(MW)	λ_t(\$/MW)	β_t(\$/MW)
1	180	25	30.6	28.5
2	160	20	31.8	30.1
3	160	20	32.1	28.9
4	180	25	29.9	28.8
5	180	25	33.5	32.3
6	200	30	38.8	36.7
7	220	30	91.4	90.1
8	240	30	83.5	82.9
9	260	40	114.8	113.5
10	300	40	76.6	75.5
11	340	40	81.3	80.2
12	300	40	68.7	67.6
13	340	40	49.8	48.6
14	350	40	69.2	67.8
15	300	40	50.8	49.4
16	280	35	51.7	50.3
17	260	35	72.9	70.1
18	240	30	68.6	66.6
19	240	30	58.1	57.7
20	220	30	60.8	59.4
21	200	30	51.2	50.1
22	190	25	55.8	54.4
23	180	25	36.6	34.7
24	180	25	32.9	30.8

Tab. 4. The total hourly necessary and non-essential partial power demand, λ and β value.

j	$k_{1,j}$	$k_{2,j}$	θ_j	CM_j(MW/h)
1	3.6	29.1	0.45	380
2	3.7	30.2	0.60	370

Tab. 5. Customer participation factor, loss coefficient and upper limit of Interruptible power.

ω_1	F(\$)	F_1(\$)	F_2(\$)
0.25	18952.7794	97207.8992	7132.2605
0.5	45033.6423	95815.9257	5748.6415
0.75	71456.5916	96955.1066	5038.9534
1	100068.7010	100068.7010	0

Tab. 6. Mean of different ω_1 results.

Based on the data given above, the proposed MSPBA is used to calculate the economic dispatch problem. We use MATLAB2012a for simulation research. The number of iterations is 1000 and the dimension is 168. In the objective function, the weight ω_1 is selected by different values. 1) When $\omega_1 = 0.5$, the two objective functions F_1 and $-F_2$ have the same weights. 2) When $\omega_1 = 1$, the objective function is the minimum total cost F_1, regardless of the benefits of consumers in the participation demand response. 3) When $\omega_1 = 0.25$, F_1 is dominant in the objective function. 4) When $\omega_1 = 0.75$, F_2 is dominant in the objective function. The objective functions of the above different weights are independently run 20 times to obtain the mean value of the results as shown in Table 6.

In Table 6, as the weight ω_1 continues to increase, the value of the objective function F and the total cost function F_1 continues to increase, and the consumer's compensation F_2 is continuously decreasing. When the weight $\omega_1 = 0.5$, the total cost function F_2 has the smallest value, that is, the cost on the power generation side is the smallest. When the demand response is not considered ($\omega_1 = 1$), the value of the objective function F is the value of the total cost function F_1 ($F = F_1 = 100068.7010$ \$) and the value of the objective function F is the largest. Combined with the data in Table 6, we can see that the total cost F_1 with considering the demand response is less than then one without considering the demand response. In summary, the model proposed in this paper can effectively reduce the cost of the power generation side.

For further explanation, this paper selects the objective function value of the weight $\omega_1 = 0.5$ for specific analysis. In Table 6, the mean value of the simulation results is the objective function $F = 45033.6423$ \$, the total cost $F_1 = 95815.9257$ \$ and the consumer compensation $F_2 = 5748.6415$ \$ when $\omega_1 = 0.5$. The optimal value of the 11th group is selected in the case of W=0.5 independent operation 20 times for specific discussion. The optimal solution for group 11 is $F = 44644.6152$ \$, $F_1 = 94962.8379$ \$ and $F_2 = 5673.6075$ \$. The power generation of each thermal generator and wind turbine at each hour is shown in Table 7. Figure 1 and 2 show the power generation of three thermal generators and two wind turbines in each hour. Table 8 details the reduced power consumption and compensation amount for each consumer's 24-hour scheduling period. It is shown that the relationship between the total cost F_1 and the number of iterations with and without considering the demand response in Figure 3.

In Table 8, it can be found that the more electricity consumers reduce, the more the amount of compensation. In each period, the unit compensation for consumers to reduce electricity consumption is different. The closer to the peak period of electricity consumption, the more unit compensation consumers receive for reducing electricity consumption. For example, in the 6th hour, the consumer 1 reduced the electricity consumption by 6.1014 MWh and the compensation amount was 223.9214 \$; In the 7th hour, the consumer 1 reduced the electricity consumption by 11.5999 MWh and the compensation amount was 1045.1150 \$; In the 9th hour, the consumer 1 reduced the electricity consumption by 14.3038 MWh and the compensation amount was 1623.4813 \$. The unit compensation amount for consumers in the 6th, 7th and 9th hours is 36.7 \$/MW, 90.1 \$/MW and 113.5 \$/MW, respectively. The above is the incentives for consumers in the demand response model.

In order to illustrate the advantages of the demand response model, Figure 3 shows a comparison of the convergence curves of the total cost function F_1 when participating in and not participating in the demand response. From Figure 3, we can see that F_1 is

t	P_1	P_2	P_2	W_1	W_2	P_{loss}
1	59.28	20.05	120.08	0.25	0.77	4.48
2	20.28	20.41	121.42	0.15	9.51	3.81
3	22.10	21.55	121.35	1.52	5.26	3.84
4	59.30	20.00	120.07	0.18	1.44	4.48
5	59.28	20.04	120.01	0.04	1.45	4.47
6	64.95	20.24	125.53	0.93	10.43	4.96
7	20.04	20.05	194.55	0.03	0.77	9.37
8	20.77	20.07	198.62	0.22	17.25	9.77
9	59.28	20.00	198.61	0.003	1.30	10.44
10	25.45	26.28	277.50	0.84	3.38	18.92
11	56.94	39.37	277.15	0.15	2.08	19.74
12	100.78	20.92	203.41	1.07	4.63	12.39
13	59.72	24.11	283.03	0.97	15.52	20.25
14	21.67	22.86	353.55	0.98	0.36	30.38
15	99.07	24.15	207.11	0.82	3.43	12.77
16	83.39	20.03	198.51	0.14	9.68	11.19
17	59.41	21.04	200.51	0.44	2.51	10.65
18	28.51	31.81	198.53	0.26	1.20	10.01
19	23.82	20.06	203.34	0.43	14.88	10.25
20	20.02	20.16	198.54	0.16	2.99	9.75
21	68.05	20.60	124.07	0.55	4.64	4.98
22	59.26	20.03	120.09	0.86	1.48	4.48
23	58.46	20.03	120.03	0.11	0.28	4.45
24	57.45	20.02	120.02	0.11	2.76	4.42

Tab. 7. Power generation of each thermal generator and wind turbine (MWh).

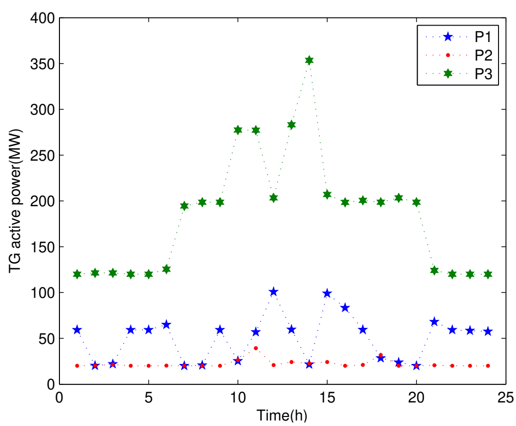

Fig. 1. Power generation of thermal generators in each period.

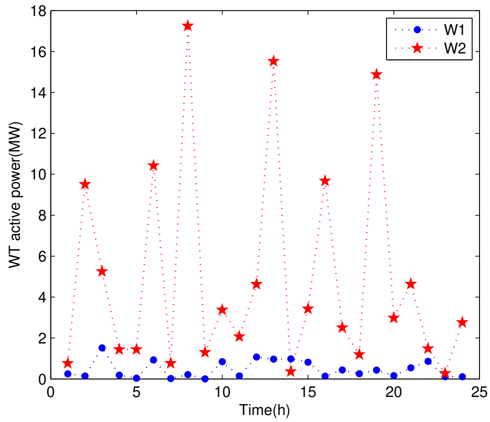

Fig. 2. Power generation of wind turbines in each period.

t	$m_{1,t}$	$y_{1,t}$	$m_{2,t}$	$y_{2,t}$
1	4.5959	130.9832	4.4595	127.0958
2	6.1196	184.2000	5.9237	178.3034
3	5.8735	169.7442	6.1972	179.0991
4	4.2433	122.2070	4.2243	121.6598
5	3.7014	119.5552	4.9548	160.0400
6	6.1014	223.9214	6.7858	249.0389
7	11.5995	1045.1150	12.3518	1112.8972
8	11.1319	922.8345	11.6992	969.8637
9	14.3038	1623.4813	16.9443	1923.1781
10	12.0188	907.4194	13.4480	1015.3240
11	12.1133	971.4867	11.9517	958.5263
12	11.3298	765.8945	10.2413	692.3119
13	7.9366	385.7188	8.9596	435.4366
14	10.0612	682.1494	10.8888	738.2606
15	9.0554	447.3368	9.1347	451.2542
16	6.6827	336.1398	7.7569	390.1721
17	10.8808	762.7441	10.8546	760.9075
18	9.7043	646.3064	9.9962	665.7469
19	8.4208	485.8802	9.2950	536.3215
20	9.0000	534.6000	8.8919	528.1789
21	8.1114	406.3811	8.9476	448.2748
22	8.7810	477.6864	8.9646	487.6742
23	4.9512	171.8066	5.6032	194.4310
24	4.0526	124.8201	5.0056	154.1725

Tab. 8. Consumers reduce electricity(MWh) and corresponding compensation($) during each period.

greatly reduced with demand response. The total cost of not considering the demand response reached 1.004E+05 \$, and the total cost of participating in the demand response was 9.412E+04 \$. In summary, under the demand response model, consumers reduce electricity consumption and receive corresponding compensation, which makes the total cost of power generation of power companies greatly reduced.

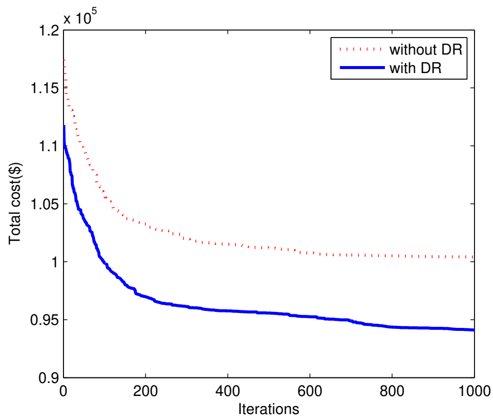

Fig. 3. Comparison of the function F_1 convergence curves of participation and non-participation in demand response.

4.2. Comparisons with other methods

To further illustrate the effectiveness of the proposed algorithm, CPLEX+YALMIP toolbox for MATLAB, DBA, BA, ILSSIWBA [10] and MSPBA are applied to the case study with $\omega_1 = 0.5$. For the sake of uniformity, the population n, loudness A_i and pulse emission rate r_i of the BA, BA, ILSSIWBA and MSPBA algorithms are set to 180, 0.5 and 0.8, respectively. The number of iterations is 1000 and the dimension is 168.

First, the CPLEX+YALMIP toolbox for MATLAB and MSPBA are used to solve the economic dispatch problem for the purpose of comparison. When $\omega_1 = 0.5$, we obtain that the objective function $F = 1.6123e{+}05$ \$, the total cost $F_1 = 3.2978e{+}05$ \$ and the consumer compensation $F_2 = 7314.2881$ \$ by the CPLEX+YALMIP toolbox for MATLAB, and the objective function $F = 45446.5149$ \$, the total cost $F_1 = 96550.3024$ \$ and the consumer compensation $F_2 = 5657.2876$ \$ by MSPBA. It is shown that MSPBA has superior performance.

Second, the computational time of CPLEX+YALMIP toolbox for MATLAB, DBA, BA, ILSSIWBA and MSPBA are 4791.2068s, 829.167s, 217.273s, 221.161s and 1058.077s, respectively (running once independently). It is observed that the CPLEX+YALMIP toolbox for MATLAB has the longest computational time, whereas BA has the shortest computational time. The computational time of MSPBA is longer than those of DBA, BA and ILSSIWBA, except that of the CPLEX+YALMIP toolbox for MATLAB. We will further improve the computational time of MSPBA in the future research.

Algorithm	Mean	Best	Worst	SD
BA	48304.7596	47476.8764	49402.9266	491.8839
DBA	49242.1948	48376.0837	50707.9592	640.5430
ILSSIWBA	46569.7784	45749.3223	47554.8438	556.5728
MSPBA	**45033.6423**	**44644.6140**	**45446.5149**	**203.6348**

Tab. 9. Comparison of four algorithms.

Third, the comparison results of DBA, BA, ILSSIWBA and MSPBA running independently for 20 times are shown in Table 9 (the best results are marked in bold). It can be seen from Table 9 that the average, optimal, worst value and standard deviation of the MSPBA optimization objective function are most superior to the other three algorithms. The results of the comparison demonstrate the effectiveness of MSPBA in dealing with economic dispatch problems.

5. CONCLUSION

In this paper, a new economic dispatch with demand response model was proposed. The demand response model divided consumers' electricity demand into necessary part and non-essential part. The part of the consumer's participation in the demand response was the non-essential part of the electricity consumption. This model took into account the minimum total cost (fuel cost, random wind power cost and emission cost) and the maximum consumer's demand response benefit while satisfying some given constraints. Then, a multi-subpopulation bat algorithm MSPBA was proposed to overcome the weakness of BA. In the proposed MSPBA, the population was divided into three subgroups for different search strategies, which were able to enhance the global search ability and accuracy of the algorithm. In the first experiment, a case of three thermal generators, two wind turbines and two consumers was demonstrated the effectiveness of using MSPBA to deal with economic dispatch problem. The results showed that the economic dispatch with demand response model could effectively reduce consumer demand for electrical energy, reduce fuel costs and emissions. Finally, the superiority of the proposed algorithm was proved by comparing with other five algorithms. In future, we will further explore computational time and stability of MSPBA dealing with complex problems, and test the effectiveness of the proposed algorithm in a larger power system with the experimental conditions.

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