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Dynamic economic dispatch for wind-thermal power system using a novel bi-population chaotic differential evolution algorithm

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ABSTRACT

Based on in-depth analysis of the stochastic nature of wind power output, the Weibull distribution parameters of regional wind speed for different time intervals are obtained respectively, and then the probability density functions of wind power output for different time intervals are achieved. These functions can be used to calculate output-overestimate and output-underestimate probabilities in each interval, so possible extra costs for maintaining the power system stability caused by incorporating unstable wind power can be calculated. Taking into account the possible costs, a stochastic optimization model for dynamic economic dispatch of wind-thermal power system is established to minimize the comprehensive operation expected cost. Moreover, a new algorithm, bi-population chaotic differential evolution (BPCDE) algorithm is proposed to solve this complicated model. The algorithm introduces bi-population evolution strategy, chaotic map update mechanism and Metropolis rule to improve the standard differential evolution algorithm. These improvements can overcome the premature problem caused by lacking of the individual diversity in the later stage of differential evolution and strengthen the global search ability of the algorithm. The validity and superiority are demonstrated by simulation results on a power system integrated with large scale wind farms.

1. Introduction

For electrical power system economic dispatch, it is called static economic dispatch (SED) while the dispatch period is only one time interval and dynamic economic dispatch (DED) while the period includes several continuous time intervals. Since DED needs to consider the internal coupling of the operation of power grid and units in each continuous time interval, there are more constraints and higher variable-dimensions and that makes it more difficult to find optimal solution than SED. However, DED can reveal the operation of power system more truly and then has more research value and practical value [1–4].

Nowadays, with rapid development of renewable energy, large scale wind power is more and more widely included in electrical power system. However, the uncontrollable wind speed leads to the uncertainty of wind power output and then the wind power output in each time interval is stochastic. The requirements for DED are at a higher level since the characteristics of wind energy are quite different from other conventional energies [5]. Therefore, in order to improve the validity and reliability of dynamic economic dispatch of electrical power system integrated with wind energy, it is necessary to consider the uncertainty output of wind energy while establishing optimal dispatch model. At present, the most used methods include wind speed forecasting [6,7], fuzzy modeling [8,9], probability analysis [10], etc. Though there have been a lot of researches on wind speed forecasting, the forecasting error is still too high to put into practice. In fuzzy modeling, wind speed is generally presented by a fuzzy number. It is feasibility to some extent but the evaluation standard is always subjective. The probability analysis achieves probability model of wind speed distribution through statistics and analysis of plenty of samples of wind speed, and then converts them into probability model of wind power output distribution. It is more feasible and more objective than fuzzy modeling. The researches have shown that two-parameter Weibull distribution curve can fit actual wind speed distribution probability function of most regions and has been widely used in wind energy analysis and wind power plant designing [11,12]. However, those researches are generally based on regional wind speed obeying one certain two-parameter Weibull distribution model in long term. The scale of long term wind speed distribution model is big and there will be great error while applying it in probability analysis in a short term. Moreover, time sequence of the change of wind speed is not considered. So these long term wind speed distribution models are not appropriate to directly be applied into dynamic economic dispatch of an electrical power system integrated with wind power. Therefore,

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the historical regional wind speed samples should be statistically analyzed interval by interval, and then adjusted according to forecasting value of wind speed. And for each time interval, the wind speed Weibull distribution model is achieved separately. These distribution models for different time intervals then are applied in establishing stochastic optimal model of dynamic economic dispatch of electrical system integrated with wind energy. Moreover, since the real outputs of wind generation unit in some time intervals do not match the scheduled outputs and the system has to add cost to maintain stability, overestimated cost and underestimated cost are introduced in this model to simulate the impact on dynamic economic dispatch caused by the uncertainty of wind power output.

The dynamic economic dispatch model including wind energy has characteristics of high dimensions, poly-constraints, stochastic variables, piecewise nonlinear, etc. It is difficult to solve the model by conventional methods such as genetic algorithm (GA), simulated annealing (SA) and gradient-based optimization. While applying GA or SA to solve this problem, the speed is slow and the convergence is unstable. On the other hand, gradient-based optimization methods are usually faster but sensitive to initial value and easy to be trapped in local-best solutions. Differential evolution (DE) is now regarded as one of the most powerful stochastic real-parameter optimization algorithms. Unlike traditional evolutionary algorithms, the mutation operator in DE is realized by the scaled differences of randomly selected and distinct population members. Therefore, no separate probability distribution has to be used, which makes the evolution completely self-organizing. Additionally, DE is very simple and easy to use as it requires only a few lines of code and takes very few control parameters in comparison with most of evolutionary algorithms. For most of non-linear optimization problems, it is proved to be better than those algorithms such as genetic algorithm, particle swarm optimization algorithm, evolution strategy, adaptive simulated annealing [13–17]. Therefore, in this paper, a new method based on DE is designed for dynamic economic dispatch model including wind energy.

2. Stochastic dynamic economic dispatch model considering wind energy

2.1. Analysis of stochastic characteristics of wind generation unit output

The output of wind generation unit is closely related to the wind speed at the height of unit hub. The power can be calculated by [18]:

$$w = \frac{1}{2} K \rho A v^3 \tag{1}$$

where w is the output of wind generation unit; K is the power coefficient of unit and it is a nonlinear function of tip speed ratio and pitch angle; ρ is air density; A is rotor swept area; and v is wind speed.

Since the nonlinear factor has little effect and can be ignored, a simplified linear piecewise function is adopted to express the relationship between output of wind generation unit and wind speed, as shown in the following equation [19]:

$$\begin{cases} w = 0, & v < v_{in} \text{ or } v > v_{out} \\ w = w_R \frac{v - v_{in}}{v_r - v_{in}}, & v_{in} \leqslant v \leqslant v_r \\ w = w_R, & v_r \leqslant v \leqslant v_{out} \end{cases} \tag{2}$$

where v_{in}, v_{out} and v_r are cut-in wind speed, cut-out wind speed and rated wind speed, respectively; w_R is the rated output power. The wind turbine maintains rated output power while the wind speed equal to or greater than v_r, and shuts down and disconnects with the power system while lower than v_{in} or higher than v_{out}.

Because of the randomicity and uncontrollability of wind speed, the output of wind generation unit also has the stochastic nature. It is generally believed that the stochastic nature of wind speed obeys two-parameter Weibull distribution [11]. To reflect the time sequence of wind speed and reduce the error of probability analysis, the wind speed distribution model adopted in this paper is the time-sharing two-parameter Weibull distribution. And then the probability density function $f_{V,t}(v_t)$ of wind speed v_t at time interval t can be expressed by (3). Several probability density function curves for Weibull distribution under different shape parameters and scale parameters are shown in Fig. 3.

$$f_{V,t}(v_t) = \frac{k_t}{c_t} \left(\frac{v_t}{c_t} \right)^{k_t - 1} \exp\left(-\left(\frac{v_t}{c_t} \right)^{k_t} \right) \tag{3}$$

where k_t and c_t are shape parameter and scale parameter of wind speed Weibull distribution model at time interval t, respectively, and which can be calculated by the mean value of wind speed μ_t and standard variance σ_t during time interval t through the following equation

$$\Gamma\left(1 + 2k_t^{-1}\right) / \Gamma^2\left(1 + k_t^{-1}\right) = (\sigma_t/\mu_t)^2 + 1 \tag{4}$$

$$c_t = \mu_t / \Gamma\left(1 + k_t^{-1}\right) \tag{5}$$

where Γ is gamma function, μ_t and σ_t are from statistics and analysis on the regional historical wind speed by time interval in recent years. The specimen bank should be updated by the newest data of wind speed. Since the inverse function of gamma function is difficult to achieve, k_t can be approximately calculated by (6) in the practical application [20].

$$k_t = (\sigma_t/\mu_t)^{-1.086} \tag{6}$$

Based on the relationship between output of wind turbine and wind speed, and according to Eqs. (2) and (3), the probability density function $f_{W,t}(w)$ of wind turbine output at time interval t can be achieved. The function is a piecewise function [10]. If wind speed obeys Weibull distribution, the cumulative probability while the output of wind turbine at time interval t, w_t, equals to 0 or rated power w_R is:

$$P_{W,t}\{w_t = 0\} = 1 - \exp\left(-\left(\frac{v_{in}}{c_t} \right)^{k_t} \right) + \exp\left(-\left(\frac{v_{out}}{c_t} \right)^{k_t} \right) \tag{7}$$

$$P_{W,t}\{w_t = w_R\} = \exp\left(-\left(\frac{v_r}{c_t} \right)^{k_t} \right) - \exp\left(-\left(\frac{v_{out}}{c_t} \right)^{k_t} \right) \tag{8}$$

The probability density function $f_{W,t}(w)$ while w_t is between 0 and w_R is:

$$\begin{aligned} f_{W,t}(w_t) = {} & \frac{k_t l v_{in}}{c_t} \left(\frac{(1 + \eta l) v_{in}}{c_t} \right)^{k_t - 1} \\ & \times \exp\left(-\left(\frac{(1 + \eta l) v_{in}}{c_t} \right)^{k_t} \right), \quad 0 \\ & < w_t < w_R, \ \eta = \frac{w_t}{w_R}, \ l = \frac{v_r - v_{in}}{v_{in}} \end{aligned} \tag{9}$$

It is clear that the probability density function of wind turbine output is more complex than that of wind speed. The function is constituted by three pieces and the sum of cumulative probability equals to 1.

2.2. The objective function of dynamic economic dispatch

2.2.1. The cost of conventional energy

The energy consumption characteristic curve of conventional energy usually can be fitted by quadric function. Moreover, the sudden open of intake valve of steam turbine would cause valve-point effect which can be reflected by adding a pulsation effect on the unit consumption characteristic curve [2]. The total consumption cost $C_{T,t}$ of n conventional generation units at time interval t is:

$$C_{T,t} = \sum_{i=1}^{n}\left(a_i + b_i p_{i,t} + c_i p_{i,t}^2 + \left|g_i \sin\left(h_i\left(p_{i,t} - p_i^{\min}\right)\right)\right|\right) \tag{10}$$

where a_i, b_i and c_i are the energy consumption characteristic parameters of the ith unit, respectively; g_i and h_i are valve-point effect parameters of the unit; $p_{i,t}$ is the scheduled output at time interval t; $p_i^{\min}$ is the minimum output of the unit.

Moreover, considering the environmental advantage of wind energy, the emission disposing or penalty should be involved. The atmospheric pollutants discharged by thermal plant mainly include CO_2, SO_2, NO_x, etc. The relationship between each atmospheric pollutant and power output can be modeled separately. Here, we adopt the atmospheric pollutants comprehensive emission model [21]. The total emission disposing cost $C_{E,t}$ of n conventional units at time interval t is:

$$\begin{aligned} C_{E,t} &= \sum_{i=1}^{n} C_{i,t}^{E} \quad \text{if } p_{i,t} = 0,\ \ C_{i,t}^{E} = 0;\ \ \text{else } C_{i,t}^{E} \\ &= 10^{-2}\left(\alpha_i + \beta_i p_{i,t} + \gamma_i p_{i,t}^2\right) + \xi_i \exp(\lambda_i p_{i,t}) \end{aligned} \tag{11}$$

where α_i, β_i, γ_i, ζ_i and λ_i are coefficients of emission cost characteristics of the ith conventional generator, which can be obtained by applying least squares method on monitoring data of unit emission to different output [22].

2.2.2. The cost of wind energy

Considering the impacts on power system caused by the uncertainty of wind energy, the wind energy cost can be divided into three parts: wind energy expected cost C_W, wind energy underestimated unbalance cost C_P and wind energy overestimated unbalance cost C_R [10]. If the wind turbine generator is not owned by the system operator, the cost expected to pay for the wind power producer can be considered as wind energy expected cost. Assume wind energy expected cost is proportional to scheduled output of wind energy generation unit, if there are m generation units in the system, then the wind energy expected cost in the tth time interval $C_{W,t}$ is:

$$C_{W,t} = \sum_{j=1}^{m} d_j w_{j,t} \tag{12}$$

where d_j and $w_{j,t}$ are the cost coefficients of the jth unit and the scheduled output of that unit at time interval t. If the wind turbine generators are owned by system operator, there is no expected cost and d_j is 0.

If the output of one certain unit is underestimated in the tth time interval, the available output of the unit will be higher than scheduled output. The system has to dispatch for power balance or else the excess power will be wasted, thus yield wind energy underestimated unbalance cost for this time interval. To determine such cost, the output-underestimate probability of each wind turbine unit should be considered according to the wind speed stochastic distribution characteristic of each location where wind turbines are installed and then calculate the wind energy underestimated unbalance cost $C_{P,t}$ by:

$$C_{P,t} = \sum_{j=1}^{m} k_{P,j}(w_{A,j,t} - w_{j,t}) = \sum_{j=1}^{m} k_{P,j}\int_{w_{j,t}}^{w_{R,j}} (w - w_{j,t}) f_{W,j,t}(w)\,dw \tag{13}$$

where $k_{P,j}$ and $w_{R,j}$ are the coefficients of underestimated unbalance cost and rated output of the jth wind turbine generator, respectively; $w_{A,j,t}$ and $f_{W,t,j}(w)$ are the available output and output probability density function of that unit at time interval t.

If the output of one unit is overestimated, the available output will be less than scheduled output, that will increase the spinning reserve capacity and cost for power balance between generators and loads in the power system, thus yield wind energy overestimated unbalance cost. While all wind turbine units' output have been determined, considering each output-overestimate probability, the total wind energy overestimated unbalance cost at time interval t can be calculated by:

$$C_{R,t} = \sum_{j=1}^{m} k_{R,j}(w_{j,t} - w_{A,j,t}) = \sum_{j=1}^{m} k_{R,j}\int_{0}^{w_{j,t}} (w_{j,t} - w) f_{W,j,t}(w)\,dw \tag{14}$$

where $k_{R,j}$ is the coefficient of overestimated unbalance cost of the jth wind turbine unit.

According to the cost analysis of conventional generators and wind turbine generators in each time interval, the objective function of dynamic economic dispatch including wind energy in T time intervals is:

$$\min\ C = \sum_{t}^{T}(C_{T,t} + C_{E,t} + C_{W,t} + C_{P,t} + C_{R,t}) \tag{15}$$

where C is the total operation expected cost of a power system including wind energy in T time intervals.

2.3. Constraints

The output of each unit should meet the constraints shown below:

$$\begin{cases} \sum_{i=1}^{n} p_{i,t} + \sum_{j=1}^{m} w_{j,t} = L_{D,t} + L_{L,t} \\ p_i^{\min} \leqslant p_{i,t} \leqslant p_i^{\max} \\ 0 \leqslant w_{j,t} \leqslant w_{R,j} \end{cases} \tag{16}$$

where $L_{D,t}$ and $L_{L,t}$ are the total demand load and the real power loss in transmission lines at time interval t, respectively; $p_i^{\min}$ and $p_i^{\max}$ are the minimum and maximum designed output of the ith conventional generator. $L_{L,t}$ has relationship with the output of each unit, line parameters, grid structure, etc., and the simplified calculation formula is [23]:

$$L_{L,t} = \sum_{i}^{n+m}\sum_{j}^{n+m} p_{i,t} B_{ij} p_{j,t} \tag{17}$$

where B_{ij} is the loss coefficient between the ith unit and the jth unit (the p in the formula should be w if the generator is a wind turbine generator).

Moreover, the conventional units should also meet constraints shown below.

2.3.1. Minimum on/off time constraints

$$\begin{cases} [T_{i,t-1}^{R} - T_{\min^i}^{R}][s_{i,t-1} - s_{i,t}] \geqslant 0 \\ [T_{i,t-1}^{S} - T_{\min^i}^{S}][s_{i,t} - s_{i,t-1}] \geqslant 0 \end{cases} \tag{18}$$

where $s_{i,t}$ represents the operation status of the ith conventional unit while 0 means the unit is offline and 1 means online. $T_{i,t-1}^{R}$ and $T_{i,t-1}^{S}$ are continuous online time and offline time of the unit during time interval $t-1$ respectively, $T^R_{\min,i}$ and $T^S_{\min,i}$ are minimum online time and minimum offline time of the unit respectively, and all in units of 1 h normally.

2.3.2. Ramping up/down rate constraints

To avoid that unit output changes too rapidly or the unit always in the process of startup or shutdown, the ramping up/down rate R has to be constrained:

$$\begin{cases} -R_i^D \leqslant (p_{i,t} - p_{i,t-1}) \leqslant R_i^U, & \text{if } p_{i,t-1} \geqslant p_i^{\min} \\ R_i^0 \leqslant |p_{i,t} - p_{i,t-1}| \leqslant R_i^1, & \text{if } 0 < p_{i,t-1} < p_i^{\min} \end{cases} \tag{19}$$

where R_i^D and R_i^U are the maximum ramping up rate and the minimum ramping down rate in normal operation, respectively; R_i^0 and R_i^1 are the upper limit and lower limit of variation rate while unit is in the process of startup or shutdown.

The dynamic economic dispatch model of a power system incorporated with wind power is formed by integrating objective function Eq. (15) and constraints mentioned above.

3. Optimization algorithm design

3.1. Improvement for differential evolution algorithm

Differential evolution algorithm is an effective and practical intelligent optimization algorithm. Description of standard DE procedure can be found in [13]. The basic operation of DE includes mutation, crossover and selection. Among which, the standard mutation is:

$$\boldsymbol{Y}_{i,G+1} = \boldsymbol{X}_{b,G} + F \cdot (\boldsymbol{X}_{r_1,G} - \boldsymbol{X}_{r_2,G}) \tag{20}$$

where $\boldsymbol{Y}_{i,G+1}$ is the intermediate individual produced by mutation; $\boldsymbol{X}_{r,G}$ is the rth individual vector; r_1 and r_2 are randomly chosen and $i \neq r_1 \neq r_2 \neq b$. The base vector $\boldsymbol{X}_{b,G}$ can be chosen randomly or be the present optimal individual vector. The second part of right side of the formula is mutation differential term and F is mutation scale factor.

Then do crossover by (21). After crossover between targeted individual $\boldsymbol{X}_{i,G}$ and intermediate individual $\boldsymbol{Y}_{i,G+1}$, a candidate individual of the next generation $\boldsymbol{Z}_{i,G+1}$ is produced to maintain diversity of population.

$$\begin{cases} X_{i,G} = [x_{i,1}, x_{i,2}, \cdots, x_{i,d}] \\ Y_{i,G+1} = [y_{i,1}, y_{i,2}, \cdots, y_{i,d}] \\ Z_{i,G+1} = [z_{i,1}, z_{i,2}, \cdots, z_{i,d}] \\ z_{i,j} = \begin{cases} x_{i,j}, & \text{if } R_j > C_R \\ y_{i,j}, & \text{else} \end{cases} \end{cases} \tag{21}$$

where $j \in \{1, 2, \ldots, d\}$; R_j is a random real number from the interval $[0,1]$ and crossover probability factor C_R is a real number from the interval $[0,1]$.

After crossover, apply a "greedy" selection pattern to select new individual.

$$\boldsymbol{X}_{i,G+1} = \begin{cases} \boldsymbol{Z}_{i,G+1}, & \text{if } F_{obj}(\boldsymbol{Z}_{i,G+1}) < F_{obj}(\boldsymbol{X}_{i,G}) \\ \boldsymbol{X}_{i,G}, & \text{else} \end{cases} \tag{22}$$

where $F_{obj}(\,)$ is the objective function.

In real application, there are several different mutation strategies and those strategies are differed by signs such as DE/rand/1, DE/rand/2, DE/best/1, and DE/local-to-best/1 [24]. The strategies, like DE/rand/1 and DE/rand/2, with mutation base vector being randomly chosen, are favorable toward global search because of diversity of individuals but with low convergence speed and without intensive local search. On the contrary, the strategies like DE/best/1 and DE/local-to-best/1, with mutation base vector being the present optimal individual, are of fast convergence because of highly directional evolution but are easy to premature because the population lacks of diversity. Moreover, in the late stage of evolution all the individuals tend to be similar and the differential term in mutation operation also tends to be zero. That would slow down or even cease the evolution. Though there are researches on improving the optimal-searching performance [17,25,26], the problem has not been perfectly settled yet. For that reason, the paper proposes some improvements to standard DE as shown below.

3.1.1. Bi-population evolution strategy

Divide population into two sub-populations. One is roughly-selecting population (RP) and the other is meticulously-selecting population (MP). RP is used for preliminary selection for numerous individuals and adopts DE/rand/1 mutation strategy as shown in the following equation:

$$\boldsymbol{Y}_{i,G+1} = \boldsymbol{X}_{r_3,G} + F \cdot (\boldsymbol{X}_{r_1,G} - \boldsymbol{X}_{r_2,G}) \tag{23}$$

where r_1, $r_2$and r_3 are randomly chosen and $i \neq r_1 \neq r_2 \neq r_3$.

That is to ensure the sub-population to maintain diversity for searching optimal solutions in solution space in full range. MP is used for further selection among the population produced after roughly selecting. It introduces jitter variation into DE/best/1 mutation strategy as shown in (24) to ensure local meticulously search in the neighborhood of the present optimal [17].

$$\boldsymbol{Y}_{i,G+1} = \boldsymbol{X}_{best,G} + [F + (1-F) \cdot rand] \cdot (\boldsymbol{X}_{r_1,G} - \boldsymbol{X}_{r_2,G}) \tag{24}$$

where *rand* is a uniformly random real number from the interval $[0,1]$, $\boldsymbol{X}_{best,G}$ is the present optimal individual vector.

Repeat replacing the worst individual in MP by the best individual in RP to update MP. At the same time, RP is updated by chaotic map shown below. This operation can ensure not only global search ability of the whole population but also meticulous local search ability.

3.1.2. Chaotic map to update population

Chaos is a ubiquitous nonlinear phenomenon in nature. It has characteristics of inherent stochastic property, sensitivity to initial condition and ergodicity. In evolution algorithm, chaotic map can be used to produce new individuals to maintain diversity of population and improve the performance of global search. Fig. 1 shows the chaotic sequence distribution of two usual maps, Logistic map and Tent map, with initial value of 0.46 and after 40,000 iterations. Obviously, the probability of two sides of the interval $[0,1]$ is much higher than that of the middle area of the interval for the Logistic map, and Tent map has better uniform ergodicity than Logistic map. Moreover, Tent map has higher computation speed. Therefore, the chaotic optimization method based on Tent map has higher efficiency than that based on Logistic map [27]. The mathematic expression of Tent map is:

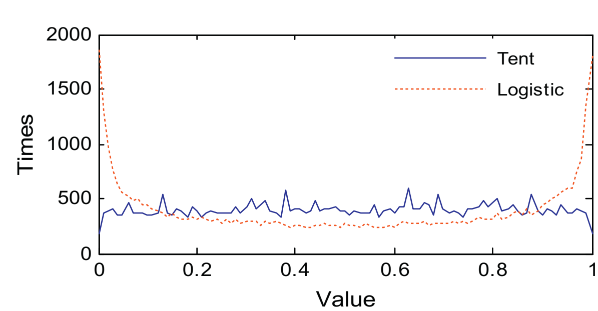

Fig. 1. The sequence distribution of Tent map and Logistic map.

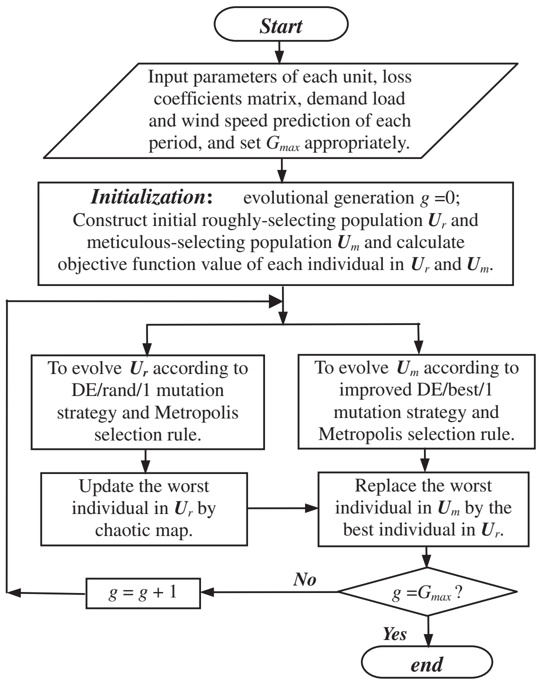

Fig. 2. Flowchart of BPCDE algorithm.

$$c_{k+1} = \begin{cases} 2c_k, & \text{if } 0 \leqslant c_k \leqslant 0.5 \\ 2(1-c_k), & \text{if } 0.5 < c_k \leqslant 1 \end{cases} \tag{25}$$

The Tent chaotic map sequence with the property of ergodicity can be produced by (25). It can be seen from Tent map iteration that the produced intermediate sequences should avoid small cycle point (e.g. $c_k = c_{k-m}$, $m = \{1,2,3,4\}$) or fixed point (e.g. $c_k = \{0, 0.25, 0.5, 0.75\}$) or else the sequence update would stop.

In this paper, the worst individuals in RP are replaced according to the new individuals' sequence produced by Tent chaotic map in the solution space.

3.1.3. Metropolis rule for selection

Since the "greedy" selection mode used in standard DE leaves no chance for any inferior individuals to be selected into the next generation which is not favorable for population to keep diversity, the Metropolis rule used in simulated annealing algorithm [28] is introduced to select new individuals. That will give chances for inferior individuals to be selected and can self-adaptively adjust the preservation probability of inferior individuals according to evolution process. The operation can be express by:

$$X_{i,G+1} = \begin{cases} Z_{i,G+1}, & \text{if } \exp\left(\frac{F_{obj}(X_{i,G}) - F_{obj}(Z_{i,G+1})}{T_M}\right) > rand \\ X_{i,G}, & \text{else} \end{cases} \tag{26}$$

where T_M is temperature-control-parameter. A relative greater value for T_M in the initial stage of evolution can increase search ability for algorithm because of greater probability of selecting inferior solutions. The value of T_M should decrease with the iteration's increase so as to be favorable for local meticulous search in later stage of evolution.

3.2. Check for individual code

It is vital for checking individual code to avoid invalid computation and increase computation efficiency.

3.2.1. Determine the output range for conventional generators

The output of conventional generator in each time interval should meet the minimum on/off time constraints and ramping up/down rate constraints, so it is related to the preceding. It can be dynamically determined based on the operation status during last interval and all the constraints. For the ith conventional generator, assume its output in time interval $t-1$ is $p_{i,t-1}$ and the current status has been maintained for T_c, after considering all the constraints, the on/off status and the range of output $p_{i,t}$ in the tth time interval, $[p_{i,t}^{\min}, p_{i,t}^{\max}]$, can be determined as follows:

(a) When $p_{i,t-1} \geq p_i^{\min}$, the ith unit should be online, and if $T_c \geq T_{\min,i}^R$, the unit is allowed to be shut down, then $p_{i,t}^{\min} = \max\left(p_{i,t-1} - R_i^D 0\right), p_{i,t}^{\max} = \min\left(p_i^{\max}, p_{i,t-1} + R_i^U\right)$; otherwise, the unit is not allowed to be shut down and $p_{i,t}^{\min} = \max\left(p_{i,t-1} - R_i^D, p_i^{\min}\right), p_{i,t}^{\max} = \min\left(p_i^{\max}, p_{i,t-1} + R_i^U\right)$.
(b) When $0 < p_{i,t-1} < p_i^{\min}$, the ith unit should be in the process of shutdown if $p_{i,t-1} < p_{i,t-2}$, and then $p_{i,t}^{\min} = \max(p_{i,t-1} - R_i^1, 0)$, $p_{i,t}^{\max} = \max(p_{i,t-1} - R_i^0, 0)$. If $0 < p_{i,t-1} < p_i^{\min}$ and $p_{i,t-1} > p_{i,t-2}$, that means the unit is in the process of startup and then $p_{i,t}^{\min} = \min\left(p_{i,t-1} + R_i^0, \max\left(q_{\min}, p_{i,t-1} + R_i^U\right)\right)$, $p_{i,t}^{\max} = \min\left(p_{i,t-1} + R_i^1, \max\left(p_i^{\min}, p_{i,t-1} + R_i^U\right)\right)$.
(c) When $p_{i,t-1} = 0$, the ith unit should be offline, and if $T_c \geqslant T_{\min,i}^S$, the unit is allowed to be started up and $p_{i,t}^{\min} = 0, p_{i,t}^{\max} = \min\left(R_i^1, p_i^{\min}\right)$; otherwise the unit is not allowed to be started up and $p_{i,t} = 0$.

3.2.2. Individual code check

First, assume that there are n thermal units and m wind turbine units in one system and the total number of time intervals in the optimal dispatch period is T. In order to meet the power balance constraint in (16), the mth wind turbine unit does not participate in the individual coding. Then the population matrix $\boldsymbol{U}$ is:

$$\boldsymbol{U} = \begin{bmatrix} u_{1,1} & u_{1,2} & \cdots & u_{1,T\cdot(n+m-1)} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,T\cdot(n+m-1)} \\ \vdots & \vdots & \ddots & \vdots \\ u_{Q,1} & u_{Q,2} & \cdots & u_{Q,T\cdot(n+m-1)} \end{bmatrix} \tag{27}$$

Each row of matrix $\boldsymbol{U}$ represents one individual code. Q is the total number of individuals of one population. Each element is a real number randomly produced from the interval $[0,1]$. The code can be converted into the output of unit in each period by:

$$\begin{cases} p_{i,t} = p_{i,t}^{\min} + u_{k,a}\left(p_{i,t}^{\max} - p_{i,t}^{\min}\right), & i = 1,2,\ldots,n \\ w_{j,t} = u_{k,b} w_{R,j}, & j = 1,2,\ldots,m-1 \\ a = (t-1)(n+m-1)+i \\ b = (t-1)(n+m-1)+n+j \end{cases} \tag{28}$$

The output of mth wind turbine unit can be achieved by:

$$\begin{aligned} w_{m,t} &= L_{D,t} + L_{L,t} - \sum_{i=1}^{n} p_{i,t} - \sum_{j=1}^{m-1} w_{j,t} \\ w_{m,t} &= \begin{cases} 0, & \text{if } w_{m,t} < 0 \\ w_{R,m}, & \text{if } w_{m,t} > w_{R,m} \end{cases} \end{aligned} \tag{29}$$

To each individual, record its total number of times N not satisfying the constraints in T time intervals, and apply (30) to give abnormal amplification for the outputs of conventional units corresponding to this individual, thus to inflict economical penalty on its objective function. Adopting this method, those unreasonable individuals will be eliminated soon in the process of evolution.

$$\begin{aligned} &\text{if } w_{m,t} < 0 \text{ or } w_{m,t} > w_{R,m}, \quad N = N + 1 \\ &p_{i,t} = p_{i,t} + N \cdot p_i^{\max}, \quad i = 1, 2, \ldots, n \end{aligned} \tag{30}$$

Then calculate the value of objective functions of all individuals in population by (15). The values are the basis of individual selection.

3.3. Design for algorithm flow

The flowchart of bi-population chaotic DE (BPCDE) algorithm proposed in this paper is shown in Fig. 2, where $G_{\max}$ is the maximum number of iteration.

The procedure of updating the roughly-selecting population $\boldsymbol{U}_r$ by chaotic map is as follows:

Step 1: When the generation $g = 0$, randomly produce chaotic initial individual $\boldsymbol{C_g} = [c_{g,1}, c_{g,2}, \ldots, c_{g,T.(n+m-1)}]$ from the interval $[0, 1]$.
Step 2: Replace the worst individual in $\boldsymbol{U_r}$ by $\boldsymbol{C_g}$.
Step 3: Avoid small cycle point or fixed point by adding small variation as shown in (31) and then produce new individual $\boldsymbol{C_{g+1}}$ by Tent Chaotic map shown in (25).

$$\begin{aligned} &\text{if } c_{g,i} = \{0,\ 0.25,\ 0.5,\ 0.75\} \text{ or } c_{g,i} = c_{g-k,i} \\ &c_{g,i} = \begin{cases} c_{g,i} + rand(0,\ 1) \times 0.1, & \text{if } c_{g,i} < 0.5 \\ c_{g,i} - rand(0,\ 1) \times 0.1, & \text{else} \end{cases} \\ &(i = \{1, 2, \ldots, T(n+m-1)\}, \quad k = \{1,\ 2,\ 3,\ 4\}) \end{aligned} \tag{31}$$

Step 4: $g = g + 1$, then back to Step 2.

In this paper, the scale of roughly-selecting population $\boldsymbol{U}_r$ is three times larger than that of meticulously-selecting population $\boldsymbol{U}_m$ in order for wider search to $\boldsymbol{U}_r$ and higher efficiency meticulously-selecting to $\boldsymbol{U}_m$. The dispatch schedule of each unit's output corresponding to best individual in the last $\boldsymbol{U}_m$ is the optimal solution of the dynamic economic dispatch problem of power system integrated with wind power.

4. Example and analysis

To verify the validity of the method in this paper, take a simplified power system with five conventional thermal power units, which are installed in five different buses in the grid, and one large scale wind farms as an example. The parameters of five thermal units are shown in Fig. 1. There are 160 wind turbines of the same type. The turbine's rated power is 1.5 MW, cut-in wind speed v_{in} = 3 m/s, rated wind speed v_r = 15 m/s and cut-out wind speed v_{out} = 25 m/s. The installation site is flat and the regional wind speed obeys Weibull distribution. The cost coefficient of wind power d is 30 $/MW h. The underestimated unbalanced coefficient k_P and the overestimated unbalanced coefficient k_R is 2.2 and 4.0 $/MW h, respectively. Since the capacity of a single wind turbine is too small, the whole wind farm would be regarded as one unit to participate into the economic dispatch. Then the total capacity of wind power is 240 MW.

In Table 1, p_0 and T_0 is the initial output and the duration of initial status of the unit, respectively. The loss coefficients are shown in Table 2.

Since the wind speed is stochastic and can only be predicted in a short term, the dispatch cycle of the power system including wind energy is short as well. In this paper, the economic dispatch period is divided into six time intervals. The load demand during each time interval can be predicted. The mean wind speed μ and standard variation σ, shown in Table 3, can be determined by recent historical wind speed data. Note that the wind speed parameters are mainly from statistical analysis on the historical wind speed data by time interval and have little effect of the prediction precise of wind speed. In theory, it can be applied into dynamic economic dispatch for longer cycle (e.g. 12 time intervals or 24 time intervals) and with little difference from six time intervals in calculation procedure.

Table 1
Parameters of thermal units.

Parameters	Units				
	U_1	U_2	U_3	U_4	U_5
a/($/h)	100	200	100	200	100
b/($/MW h)	15	18	10	18	15
c/($/MW^2 h)	0.12	0.04	0.06	0.04	0.05
g/($/h)	260	280	300	270	380
h/(rad/MW)	5.2	6.3	8.6	9.8	4.2
α/($/h)	911.8	613.1	628.5	542.6	461.3
β/($/MW h)	−2.094	−5.457	−4.116	−8.550	−9.712
γ/($/MW^2 h)	0.05859	0.04266	0.03669	0.0238	0.01153
ζ/($/h)	0.1	1	1	1	1
λ/(MW)	0.008	0.0031	0.003	0.0023	0.002
$p^{\min}$/MW	30	100	100	250	300
$p^{\max}$/MW	400	600	650	800	1000
R^D/MW	100	100	120	200	200
R^U/MW	100	100	120	180	200
R^0/MW	50	80	80	100	100
R^1/MW	100	160	160	200	300
$T^R_{\min}$/h	4	3	4	4	4
$T^S_{\min}$/h	3	3	4	3	3
p_0/MW	260	400	320	480	600
T_0/h	3	5	3	3	6

Table 2
Loss coefficients ($B_{ij}/10^{-4}$).

B_{i1}	B_{i2}	B_{i3}	B_{i4}	B_{i5}	B_{i6}
7.075	−1.005	−1.865	−1.975	−1.585	−0.360
−1.005	11.355	0.055	−1.070	−1.475	−0.510
−1.865	0.055	7.295	2.905	0.080	−0.945
−1.975	−1.070	2.905	3.960	0.395	−1.030
−1.585	−1.475	0.080	0.395	1.610	−0.535
−0.360	−0.510	−0.945	−1.030	−0.535	3.140

Table 3
L_D, μ and σ of wind speed in each period.

	Time interval					
	1	2	3	4	5	6
L_D/MW	1900	1952	2260	2330	2406	2026
μ/(m/s)	12.10	14.07	8.52	10.23	4.86	6.52
σ/(m/s)	7.03	9.29	5.13	6.85	2.91	4.28

The curves of Weibull distribution probability density functions of wind speed in each time interval can be achieved by (5) and (6) and are shown in Fig. 3.

By the improved BPCDE algorithm and the dynamic economic dispatch model considering the stochastic nature of wind power, the optimal dynamic economic dispatch scheme can be achieved and is shown in Table 4. In Table 4, p_i is the scheduled output of each thermal unit, w is the scheduled output of wind energy. The comprehensive operation expected cost C of this scheme is 793,803$.

The optimal dynamic economic dispatch scheme achieved by standard differential evolution algorithm is shown in Table 5 and its comprehensive operation expected cost C is 797,393$. It is clear that the algorithm proposed by this paper can lower the comprehensive operation expected cost effectively.

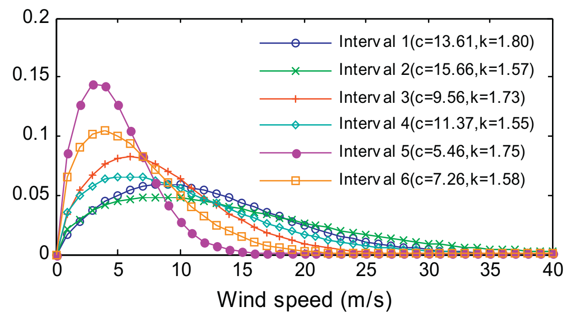

Fig. 3. Probability density functions curves for the Weibull wind speed distributions.

Table 4
Optimal load dispatch by BPCDE (MW).

	Time interval					
	1	2	3	4	5	6
p_1	330.26	349.61	388.28	392.51	399.15	333.28
p_2	354.32	333.37	420.63	423.14	457.51	359.82
p_3	277.18	261.05	283.4	301.26	249.41	273.89
p_4	476.98	454.51	519.6	568.99	667.36	475.68
p_5	575.44	648.53	838.6	861.74	941.02	754.83
w_1	105.47	100.32	87.55	92.064	49.899	63.988
L_L	219.65	195.4	278.06	309.71	358.36	235.49

Table 5
Optimal load dispatch by DE (MW).

	Time interval					
	1	2	3	4	5	6
p_1	359.91	284.79	384.01	384.66	399.86	320.6
p_2	335.4	338.46	435.56	454.73	461.87	389.2
p_3	284.14	235.61	268.44	256.5	261.46	318.4
p_4	441.61	513.51	563.63	603.08	608.06	408.08
p_5	576.06	688.23	813.12	851.29	972.47	777.23
w_1	104.47	105.56	88.694	93.898	46.738	65.528
L_L	201.59	214.16	293.46	314.15	344.46	253.04

Moreover, the evolution process comparisons among bi-population chaotic differential evolution (BPCDE), standard differential evolution (DE), particle swarm optimization (PSO) and chaotic particle swarm optimization (CPSO) [29] are shown in Fig. 4. Fig. 4 shows the best result after 10 runs of each algorithm. The mean values and variances of the algorithms final values are shown in Table 6. The scale of population is 400 in PSO, CPSO and DE, and the scale of Ur and Um in BPCDE are 300 and 100, respectively. It can be seen that the comprehensive operation expected cost C

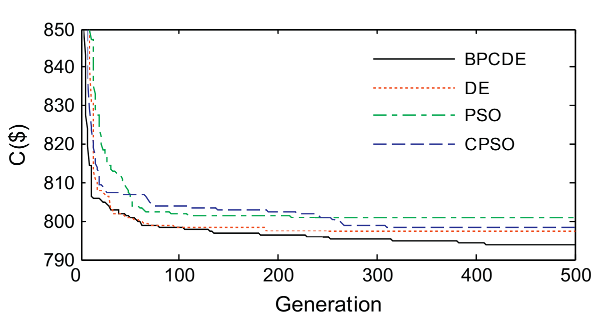

Fig. 4. Evolution process comparisons.

Table 6
Statistical analysis of the algorithms final values.

	BPCDE	DE	PSO	CPSO
Mean value/$	795,194	798,891	802,386	799,258
Variance/$^2	127134.8	135338.3	213647.1	134912.6

achieved by PSO and CPSO are 800,825$ and 798,098$, respectively. The results of both algorithms are worse than that of DE. However, in the evolution process of standard DE, the diversity of individuals is quickly lost, and then the algorithm is unable to jump out of local optimal and is easy to premature. The BPCDE algorithm applies bi-population evolution strategy, chaotic map for updating and Metropolis rules for selection, thus to maintain the diversity of individuals in the evolution process and give attention to both global search and local search, then it can jump out of local optimal constantly to prevent premature and approximate to the global optimal solution. It can also be seen from Table 6 that both mean value and variance of BPCDE are the smallest, which further proved that BPCDE has not only better performance of seeking the optimal solution but also better stability.

5. Conclusions

In this paper, the generation cost and environmental cost of thermal unit and the probability of increasing cost caused by output stochastic of wind energy are comprehensively considered, and then establish the stochastic optimization model for dynamic economic dispatch of power system integrated with wind energy. By introducing bi-population evolution strategy, chaotic map and Metropolis rules for selection into differential evolution algorithm, design a bi-population chaotic differential evolution algorithm for the optimization model. The example shows that the method can lower comprehensive operation expected cost for thermal-wind integrated system efficiently and provide scientific advice for dynamic economic dispatch of a power system integrated with large scale wind farms.

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