Research Article

Monthly Unit Commitment Model and Algorithm with Renewable Energy Generation Considering System Reliability

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With the sustained growth in renewable energy penetration, it is important to incorporate the interval prediction information of the wind and photovoltaic power into the monthly unit commitment model and introduce the system reliability rate as an indicator to measure the system reliability, which make an important contribution to deal with the volatility and randomness of the wind and photovoltaic power and ensure the economy and reliability of the monthly unit commitment. To enhance the practicality of the model and improve the solving ability, the multiobjective function composed by operating cost and reliable rate is transformed into a single-objective function by using the evaluation function based on geometric weighting method. An adaptive genetic algorithm (AGA) is used to solve the above problem when the prohibiting inbreeding strategy is adopted to replace the mutation operator, avoiding the hybridization between close relatives and containing the diversity of the population. Finally, the testing systems verify the validity and accuracy of the proposed model and algorithm.

1. Introduction

In order to cope with the global warming and environmental pollution, the proportion of renewable energy replacing traditional fossil energy generation has increased year by year. Meanwhile, renewable energy represented by wind power and photovoltaic power has attracted much attention (see [1] for more detail). However, the intermittent and uncertainties of renewable energy lead to the volatility and randomness of power from wind farms and photovoltaic power stations. Large-scale wind and solar grid-connected power generation makes the scheduling problem of power systems more complicated. Currently most of the electric energy is still provided by thermal power units with long start-off period and high start-off cost, which determines that the units should not adopt the frequent start-off scheduling mode. The monthly unit commitment (UC) making an overall consideration of power grid operation in a longer time span is adopted as medium and long-term resource optimization in [2], which could provide demand information for the monthly centralized trading power market.

The monthly UC problem refers to the establishment of a reasonable start-off scheme with minimum cost or consumption during the long-term scheduling period (this paper chooses one month as the period), thereby achieving load demand and meeting certain constraints and reserve requirements. As a large-scale mixed-integer nonlinear programming problem, monthly UC is difficult to obtain a theoretical global optimal solution while the stochastic characteristics of wind and photovoltaic power further increase the difficulty of solving the problem. At present, the forecasting technologies for wind power and photovoltaic power generation are mainly short-term and ultra-short-term forecasts including point and scenario prediction which are mostly used in the day-ahead UC models. And [3, 4] indicate that it is difficult to accurately predict the wind power and photovoltaic power output of each hour during the month before the month. Therefore, this paper introduces the interval prediction information of a month's wind and photovoltaic power output, selects the appropriate confidence level, and formulates the monthly UC scheme within a certain confidence interval, thus ensuring the economy and reliability of the operating system.

Due to the diversity of the monthly UC problem in the establishment of the objective functions and the optimization of the results, the related researches have never been
interrupted. Regarding the establishment of the objective functions, most of the traditional UC problems [5, 6] mainly consider system economy; that is, the target of monthly UC is the total operating cost of the system. After the market-oriented reforms of the power industry, the objective function deducts the lowest cost of purchasing electricity or the largest total social income reflecting the efficiency of resource allocation (see [7–9]). At the same time, with the environmental problems getting more and more attention, the emission of pollutants has become one of the optimization targets in [10]. In contrast, there are relatively few studies on the reliability of monthly UC model. In [11], the total cost of purchasing the spinning reserve is taken as the objective function, while the effects of the random outage rate and the fuel microincrement rate are comprehensively considered in the solving process to organically combine system reliability and economy. In [12], considering the factors affecting system reliability such as unit failure and random load fluctuation, a comprehensive cost model of power system operation in the scheduling period is constructed based on the cost of thermal power operation, the compensation cost caused by shutdown or power shortage, and the cost of starting up consumption. In general, the above models all integrate the system reliability into the operating cost that is integrated into the total cost of the system, which leads to the proportion of system economy and reliability cannot be adjusted in real time to meet the needs of the actual execution scenarios.

At present, the relatively mature methods for solving UC problems are priority list, dynamic programming, Lagrangian relaxation, and other traditional solving methods, as well as artificial intelligence algorithms such as particle swarm optimization and genetic algorithm (GA). Among them, the priority list realizes simple calculation speed but the obtained result tends to deviate greatly from the optimal solution in [13]; the dynamic programming in [14] is easy to fall into the “dimensional disaster” when the problem scale increases; the Lagrange relaxation in [15] limits its further application due to the problems of “dual gap” and “relaxation constraint”; there are two solving ways of the particle swarm optimization algorithm in [16]: optimizing the start-off status and decomposing the UC problem into two subproblems of unit start-off and economic dispatching optimization; in [17] GA is essentially an unconstrained optimization algorithm whose efficiency is greatly affected by how to deal with constraints; meanwhile, as it is a stochastic optimization algorithm, it requires a large amount of computation and a long time to hardly obtain a local optimal solution.

In view of the shortcomings of existing models and algorithms, this paper establishes a monthly UC model which comprehensively takes into account the economy and reliability of the power system operation. Firstly, the reliable rate of operating system is defined by integrating the margin of power supply and statistics of units start-off number, which is used as the standard to measure the reliability of system operation. Then the multiobjective functions are simultaneously composed of reliable rate and the total operating cost of power generation. Since the multiobjective programming functions conflict with each other, there is generally no optimal solution for achieving the best of all targets at the same time. In order to simplify the solving process, the multiobjective function is transformed into a single-objective programming model containing weights by using the evaluation function based on geometric weighting method, so that the dependence of system operation on economy and reliability could be adjusted in real time by adjusting the weight. Then the above model is solved by adaptive genetic algorithm (AGA) which based on the prohibiting inbreeding strategy, so that the monthly UC problem could obtain the optimal solution more accurately and efficiently. Finally, the practicality and effectiveness of the proposed model and algorithm are verified by power systems of 10–100 units.

2. Interval Prediction Information Analysis of Renewable Energy

Using medium-term weather information and combining factor analysis with probabilistic prediction of quantile regression neural network, the deterministic median prediction results and confidence intervals under different confidence levels are obtained in [18], which can effectively predict the renewable energy generation dominated by weather and the load in a long time span. The specific prediction technology would not be discussed in detail in this paper. With the increasing confidence of probability prediction, the range of confidence interval of the predictive value will also expand, which leads the actual value more likely to fall into the confidence interval. Therefore, considering the actual application, this paper selects the confidence interval of monthly wind power and photovoltaic power under 90% confidence, so that the actual predictive value falls into the confidence interval as much as possible to ensure the reliability of the monthly UC. The interval predictions of the wind farm and photovoltaic power station generation with a confidence probability of 90% are, respectively, shown in Figures 1 and 2. It should be noted that if the power system contains multiple wind farms and photovoltaic power stations, they should be combined into a single wind farm and photovoltaic power station for more convenient analysis.

3. Monthly UC Model Considering System Reliability

In order to simultaneously consider the economy and reliability of the long-term UC problem with renewable energy generation, this paper constructs a multiobjective programming model with total operating cost and reliable rate. Then the geometric weighting method is used to transform the multiobjective function for obtaining a new evaluation function that makes the computing process easier.
3.1. Objective Function

3.1.1. Optimization Goal 1: Total Operating Cost of the Power System

\[ C = \sum_{t=1}^{T} \sum_{j=1}^{N} [F(P_{jt}) + SC_{jt}] \]  

\[ F(P_{jt}) = a_{j}P_{jt}^{2} + b_{j}P_{jt} + c_{j} \]  

\[ SC_{jt} = \begin{cases} C_{j}^{\text{hot}}, & T_{\text{off}}^{j} \leq T_{\text{down}}^{j} + T_{\text{cold}}^{j} \\ C_{j}^{\text{cold}}, & T_{\text{off}}^{j} > T_{\text{down}}^{j} + T_{\text{cold}}^{j} \end{cases} \]  

where \( C \) is the total power generation cost; \( T \) is the number of periods of one cycle which takes \( T = 720 \) (each time period is 1 h); \( N \) is the total number of thermal power units; \( F(P_{jt}) \), \( SC_{jt} \), and \( P_{jt} \) are the total fuel cost, start-off cost, and active output of thermal power unit \( j \) during time period; \( a_{j} \), \( b_{j} \), \( c_{j} \) are characteristic parameters of generation cost of unit \( j \) and they are all positive; \( C_{j}^{\text{hot}} \) and \( C_{j}^{\text{cold}} \) are hot and cold start cost; \( T_{\text{off}}^{j} \) is the continuous downtime of unit \( j \); \( T_{\text{down}}^{j} \) is the minimum downtime of unit \( j \); \( T_{\text{cold}}^{j} \) is the cold start time.

3.1.2. Optimization Goal 2: Reliability of the Power System

Statistics of units start-off number

\[ \beta = \sum_{t=1}^{T} \sum_{j=1}^{N} |X_{jt}^{t} - X_{jt}^{t-1}| \]  

where \( X_{jt}^{t} \), \( X_{jt}^{t-1} \) are the start-off status of the \( j \)th unit in the \( t \) and \( t-1 \) time period, respectively. If there is a change in start-off status, the index \( \beta \) is incremented by 1. Therefore, the smaller \( \beta \) is, the more reasonable the UC is, which avoids unnecessary switching.

(2) Margin of power supply

\[ \alpha = \sum_{t=1}^{T} I(t) \]  

\[ I(t) = \begin{cases} 1, & \sum_{j=1}^{N} P_{jt}^{L} \cdot X_{jt}^{t} < P_{t}^{L} \\ 0, & \sum_{j=1}^{N} P_{jt}^{L} \cdot X_{jt}^{t} \geq P_{t}^{L} \end{cases} \]  

where \( P_{jt}^{L} \) is the rated power of the thermal power unit \( j \); \( P_{t}^{L} \) is the total load demand at time \( t \). \( \alpha \) is defined as the evaluation index that the total rated power of the system is greater than or equal to the total load demand to measure the margin of power supply. When the total rated power of the system at time \( t \) is greater than or equal to the total load demand, \( I(t) \) is taken as 0; otherwise, it is taken as 1. Therefore, the smaller \( \alpha \) is, the more sufficient the power supply is and the higher reliable of the system will be.

In the process of solving the start-off status of units in real time, there are only 0 and 1 status for each thermal power unit where 0 means the unit is out of service while 1 means the unit is running. Therefore, the comparison between the pseudo random number and the forced failure rate is used to determine the operating status of units. Under the premise that all prediction curves of the load and renewable energy output are known, the above two indexes are integrated to define the reliability of the power system:

\[ R = \frac{(a\beta/N + b\alpha)}{T} \]  

\( a \geq 0, b \geq 0, a + b = 1 \)  

where \( a, b \) are the weights of the indexes including unit start-off number and the margin of power supply, respectively. The relative proportion of \( a \) and \( b \) could be adjusted to indicate the degree of emphasis on different indexes.

3.1.3. Multiobjective Joint Optimization

The multiobjective programming functions conflict with each other and generally there is no optimal solution. In this paper, the evaluation function based on geometric weighting method [19] is used to transform the multiobjective function into a single-objective function. A solution that is more in line with the actual
situation is obtained when the weights are adjusted according to different execution scenarios. The specific steps are as follows.

(1) Normalization of the objective function

Unifying dimension, based on the maximum value \( f_{e, \max} \) and minimum value \( f_{e, \min} \), each objective function \( f_e \) \((e=1,2,\ldots,m)\) is normalized by (7) where \( x \) is the solution.

\[
\varphi_e(x) = \frac{f_e(x) - f_{e,\min}}{f_{e,\max} - f_{e,\min}} \quad (7)
\]

(2) Weights distribution of the objective function

A set of weights \( r_e (e=1,2,\ldots,m) \) corresponding to the objective function \( \varphi_e \) are given according to the importance of each objective function when \( r_e > 0 \) and \( \sum_{e=1}^{m} r_e = 1 \).

\[
u(f(x)) = \prod_{e=1}^{m} \varphi_e(x)^{r_e} \quad (8)
\]

(3) Solving a single-objective function

\[
\min \prod_{e=1}^{m} \varphi_e(x)^{r_e} \quad s.t. \quad x \in X
\]

where \( X \) is the solution set of single-objective function.

According to the above-mentioned rules of geometric weighting method for solving the multiobjective programming, the single-objective function corresponding to (1) and (6) could be obtained:

\[
\begin{align*}
\min \quad & CR = C_1(p)^{r_1} R_2(p)^{r_2} \\
\text{s.t.} \quad & p \in P
\end{align*}
\]

where \( p \) is the feasible solution of the objective function \( CR; P \) is the solution set containing all feasible solutions; \( C_{\min}, \ C_{\max} \) are the minimum and maximum value of the objective function \( C(p) \), respectively; \( R_{\min}, \ R_{\max} \) are the minimum and maximum value of objective function \( R(p) \), respectively; \( C_1(p), \ R_1(p) \) are the normalized functions of the objective functions \( C(p) \) and \( R(p) \), respectively; \( r_1, \ r_2 \) determined by the degree of dependence on system economy and reliability are the weights of functions \( C_1(p) \) and \( R_1(p) \), respectively.

3.2. Constraints

(1) Positive and negative spinning reserves are as follows.

Spinning reserve is the reserved capacity of the specified units to ensure the reliability of the system operation. The monthly UC problem combined with wind, solar, and thermal power generation involves the upper and lower limits of interval prediction of wind power and photovoltaic power. When the load is maximum and the renewable energy generation output is minimum, it may lead to the positive spinning reserve required by the system, as shown in equation (11); when the load is minimum and the renewable energy generation output is maximum, it may lead to the negative spinning reserve required by the system, as shown in (12).

\[
\begin{align*}
\sum_{j=1}^{N} p_{jl}^\max + p_{Wt} + P_{St} - p_{l}^{Rh} & \geq P_{l}^L \quad (11) \\
\sum_{j=1}^{N} p_{jl}^\min + p_{Wt}^\min + P_{St}^\max + p_{l}^{Rr} & \leq P_{l}^L \quad (12)
\end{align*}
\]

where \( p_{jl}^\max, \ p_{jl}^\min \) are the maximum and minimum active output of unit \( j \) during \( t \) time period; \( P_{l}^L \) is the total load demand during \( t \) time period; \( P_{Wt}^\max, \ P_{Wt}^\min \) are the upper and lower limits of wind power prediction during \( t \) time period, respectively; \( P_{St}^\max, \ P_{St}^\min \) are the upper and lower limits of photovoltaic power prediction during \( t \) time period, respectively; \( P_{l}^{Rh}, \ P_{l}^{Rr} \) are the positive and negative spinning reserves during \( t \) time period, respectively, and both of their values are the 10% of total load \( P_{l}^L \) during \( t \) time period.

(2) Minimum start-off time is as follows:

\[
\begin{align*}
T_{j}^s & \geq T_{j}^{up} \\
T_{j}^t & \geq T_{j}^{down}
\end{align*}
\]

where \( T_{j}^s, \ T_{j}^t \) are the continuous start-off time of unit \( j; \ T_{j}^{up}, \ T_{j}^{down} \) are the minimum start-off time of unit \( j \).

(3) Real-time power balance during \( t \) time period is as follows:

\[
\sum_{j=1}^{N} p_{jl} + P_{Wt} + P_{St} = P_{l}^L
\]

(4) The upper and lower limits of the thermal power units output during \( t \) time period are as follows:

\[
p_{jl}^{\min} \leq p_{jl} \leq p_{jl}^{\max}
\]

where \( p_{jl} \) is the active output of the thermal power unit \( j \) during \( t \) time period.

(5) The upper and lower limits of the wind farm output during \( t \) time period are as follows:

\[
0 \leq P_{Wt} \leq P_{Wt}^\max
\]

where \( P_{Wt}^\max \) is the rated wind power.

(6) The upper and lower limits of the photovoltaic power station output during \( t \) time period are as follows:

\[
0 \leq P_{St} \leq P_{St}^\max
\]

where \( P_{St}^\max \) is the rated photovoltaic power.
(7) Since the monthly unit commitment belongs to the medium and long-term scheduling category, the accuracy of line power flow calculated under the whole month is poor. Therefore, the transmission constraint instead of the network constraint is adopted [20]. The power limit of transmission section is as follows:

\[
\sum_{j \in \Psi_c} p_{jt}^{\text{max}} + p_{wt}^{\text{max}} + p_{st}^{\text{max}} - p_t^L \leq P_{ct}
\]

where \(\Psi_c\) represents the unit set of transmission section \(c\); \(P_{ct}\) is the maximum transmission power of transmission section \(c\).

4. Solving Monthly UC Model Based on AGA

The optimization objective function established in this paper belongs to a large-scale nonconvex mixed-integer nonlinear programming problem involving discrete and continuous variables. As a random search optimization algorithm, genetic algorithm (GA) could effectively solve large-scale scheduling problems. However, the traditional GA has some shortcomings such as premature problem and slow convergence speed. Therefore, this paper uses an improved adaptive genetic algorithm (AGA) based on the prohibiting inbreeding strategy to improve the calculative efficiency.

Coding is the primary problem to be solved by applying AGA. This paper selects (10) as the fitness function and records each individual as \(p\) when the \(N \times T\) binary matrix is used to represent the operating status of \(N\) thermal power units in \(T\) time periods. The population size is recorded as \(P_t\), the number of iterations is \(G\), and the crossover rate and mutation rate are \(P_c\) and \(P_m\), respectively. The traditional GA applies the selection operator, the crossover operator, and the mutation operator to the group, respectively; meanwhile, each time more individuals with higher adaptability are inherited to the next generation according to the rule of "survival of the fittest". In this way, repeated iterations ultimately result in a good individual among the population, which achieves a phenotype that is at or close to the optimal solution of the problem. However, in the later iterative process the GA is prone to generate more close relatives, which makes the diversity of the population destroyed. Therefore, (19) is adopted in this paper to represent the degree of intimacy and the mutation probability is adaptively selected by the closeness among the individuals, so as to avoid the unreasonable selection of the mutation probability affecting the stability of the algorithm.

\[
S = \frac{\sum_{k=1}^{N \times T} f_k L_k}{\sum_{k=1}^{N \times T} f_k}
\]

where \(S\) is the intimacy; \(N \times T\) is the length of the gene; \(f_k\) is the weight of the locus. \(L_k\) takes 1 when the values of the same loci are the same, otherwise 0.

According to the central limit theorem, the probability of mutation conforms to the normal distribution, so the probability density function between the mutation rate \(P_m\) and the intimacy \(S\) is shown as

\[
P_m = \int_{-\infty}^{S} f(x)dx
\]

\[
f(x) = \frac{1}{\sqrt{2\pi}S}\exp\left[\frac{-(x-P_{m0})^2}{2S}\right]
\]

where \(P_m\) is the mutation probability; \(P_{m0}\) is the initial mutation probability. The relationship between the mutation probability \(P_m\) and the intimacy \(S\) is shown in Figure 3 which indicates that the \(P_m\) adapts to \(S\).

Using the above-mentioned prohibiting inbreeding strategy to replace the mutation operator in the traditional GA, the flowchart of the AGA is shown in Figure 4.

5. Simulation

The algorithm proposed in this paper is applied to respectively simulate the monthly UC with 10, 20, 40, 60, 80, and 100 units connected to the same transmission section. The units parameters of the 10-unit system are detailed in [21] when the total load of each period is shown in Figure 5. The units parameters of the 20-unit system could be obtained by copying the units parameters of the 10-unit system; meanwhile, the load and wind-solar power generation of the 20-unit system are twice as much as that of the 10-unit system. Similarly, data for 40, 60, 80, and 100 units systems could be generated.

Considering the randomness of AGA, this paper calculates 30 times for each initial population. The size of the population is 20 and the time periods is 720 when the mutation and crossover rate are, respectively, selected as 0.005 and 0.75. Programming with MATLAB, the testing process is performed under the operating environment of CPU i5-3337U 1.8GHz and memory of 4.00G.
The monthly UC model is tested on the premise of considering the characteristics of wind-solar random generation. When only the total operating cost of the system is taken as the objective function, Figure 6 shows the convergence curve of the 10-unit system obtained by AGA and the traditional GA. From the perspective of the optimal value of operating cost, since the traditional GA is easy to fall into the local optimum, the solution of the algorithm in this paper is 1.4982 × 10^7$ while that of the traditional GA is 1.5166 × 10^7$; that is, the results obtained by AGA are better than those obtained by traditional GA; from the perspective of the convergence speed of the algorithms, in the computing process, only when the iterative number of traditional GA reaches 100 it could be stable around the optimal value; the algorithm in this paper has already converged when it has been iterated 50 times. The reason is that traditional GA has serious premature phenomenon while AGA could effectively maintain the diversity of the population and improve the premature phenomenon to a certain extent, which makes the convergence speed of AGA significantly faster and improves the computational efficiency and saves computing time.

<table>
<thead>
<tr>
<th>unit</th>
<th>Forced failure rate</th>
<th>unit</th>
<th>Forced failure rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0012</td>
<td>6</td>
<td>0.0012</td>
</tr>
<tr>
<td>2</td>
<td>0.0021</td>
<td>7</td>
<td>0.0021</td>
</tr>
<tr>
<td>3</td>
<td>0.0025</td>
<td>8</td>
<td>0.0025</td>
</tr>
<tr>
<td>4</td>
<td>0.0038</td>
<td>9</td>
<td>0.0038</td>
</tr>
<tr>
<td>5</td>
<td>0.0028</td>
<td>10</td>
<td>0.0028</td>
</tr>
</tbody>
</table>
### Table 2: Results of weights assignment.

<table>
<thead>
<tr>
<th>$r_1$</th>
<th>$r_2$</th>
<th>$R$</th>
<th>$C$</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>0.8</td>
<td>0.0416</td>
<td>15566805</td>
<td>0.5034</td>
</tr>
<tr>
<td>0.4</td>
<td>0.6</td>
<td>0.0663</td>
<td>15334710</td>
<td>0.3799</td>
</tr>
<tr>
<td>0.5</td>
<td>0.5</td>
<td>0.0729</td>
<td>15149632</td>
<td>0.2596</td>
</tr>
<tr>
<td>0.6</td>
<td>0.4</td>
<td>0.0988</td>
<td>15080933</td>
<td>0.2584</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>0.1402</td>
<td>14969227</td>
<td>0.2279</td>
</tr>
</tbody>
</table>

The economy and reliability have different meanings for different power systems or different operating scenes of the same power system. Therefore, this paper evaluates the system economy and reliability by assigning different proportions to the weights $r_1$, $r_2$ and calculating the total cost and reliability with the formula (10) as the objective function. The specific calculation results are shown in Table 2 which indicates that the value of total cost will be relatively low and the economy will be higher when $r_1$ accounts for a large proportion; the value of reliable rate will be relatively low and the reliability will be higher when $r_2$ accounts for a large proportion. And the value of overall optimal function which is not necessarily related to distributions of the weights is better when the system economy occupies a more important position.

When the reliability and economy play the same important role in the power system which means $r_1 = r_2$, the optimal value, the worst value, and the average value of the optimized cost as well as the reliable rate of the operating system and the average running time of 30 calculations obtained by AGA, traditional GA, and BBO (see [22]) of the 10, 20, 40, 60, 80, and 100 units systems are shown in Table 3. It could be indicated from Table 3 that the proposed algorithm has lower total cost and higher operational reliability than the other two algorithms and the superiority of the running time is more obvious with the increment of the population size.

### 6. Conclusion

In order to ensure that the monthly UC problem has the ability to cope with the uncertainty of the renewable energy generation and balance the economy and reliability of the system operation as well as improve the solving efficiency, the main work done in this paper is as follows:

1. Based on the interval prediction information of the mid-term power output of wind farms and photovoltaic power stations, the positive and negative spinning reserves and power balance of wind-photovoltaic-thermal power generation are processed. At the same time, the system reliable rate which is integrated by power supply margin and unit start-off statistics is introduced. The reliable rate and the total operating cost of the system constitute a multiobjective optimal model which takes into account the characteristics of wind and photovoltaic power generation.

2. Using the geometric weighting method to transform the multiobjective functions into a single-objective function, the different dependence on the economy and reliability of the system is adjusted by the weights.

3. Judging the blood relative degree of the hybrid individuals according to the intimacy and reasonably selecting the mutation probability, the monthly UC problem is solved by the AGA based on the prohibiting inbreeding strategy, which effectively saves the total operating cost and improves the system reliability while maintaining the diversity of the population.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.
Table 3: Calculation results.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Results</th>
<th>AGA</th>
<th>GA</th>
<th>BBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>optimal cost/10^5 $</td>
<td>1.5037</td>
<td>1.5106</td>
<td>1.5137</td>
</tr>
<tr>
<td>10</td>
<td>worst cost/10^5 $</td>
<td>1.5525</td>
<td>1.5429</td>
<td>1.5525</td>
</tr>
<tr>
<td>units</td>
<td>average cost/10^5 $</td>
<td>1.5290</td>
<td>1.5366</td>
<td>1.5390</td>
</tr>
<tr>
<td></td>
<td>time/s</td>
<td>68</td>
<td>62</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>reliable rate</td>
<td>0.0883</td>
<td>0.0985</td>
<td>0.0993</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>optimal cost/10^5 $</td>
<td>3.1003</td>
<td>3.1068</td>
<td>3.1163</td>
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<td>units</td>
<td>worst cost/10^5 $</td>
<td>3.2806</td>
<td>3.2907</td>
<td>3.2904</td>
</tr>
<tr>
<td></td>
<td>average cost/10^5 $</td>
<td>3.2066</td>
<td>3.2512</td>
<td>3.2566</td>
</tr>
<tr>
<td></td>
<td>time/s</td>
<td>138</td>
<td>136</td>
<td>148</td>
</tr>
<tr>
<td></td>
<td>reliable rate</td>
<td>0.0916</td>
<td>0.1005</td>
<td>0.1016</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>optimal cost/10^5 $</td>
<td>6.3677</td>
<td>6.3881</td>
<td>6.3907</td>
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Note: BBO is biogeography-based optimization algorithm.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References


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