Hindawi
Mathematical Problems in Engineering
Volume 2019, Article ID 3835296, 9 pages
https://doi.org/10.1155/2019/3835296

Research Article

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

Yongli Zhu, Xuechun Liu, Yujia Zhai, and Ran Deng

State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Baoding 071003, China

Correspondence should be addressed to Xuechun Liu; lxc13722958050@163.com

Received 15 January 2019; Accepted 28 March 2019; Published 10 April 2019

Academic Editor: Hong-Yu Wu

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 reliable 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, 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 the power output of the units simultaneously 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.

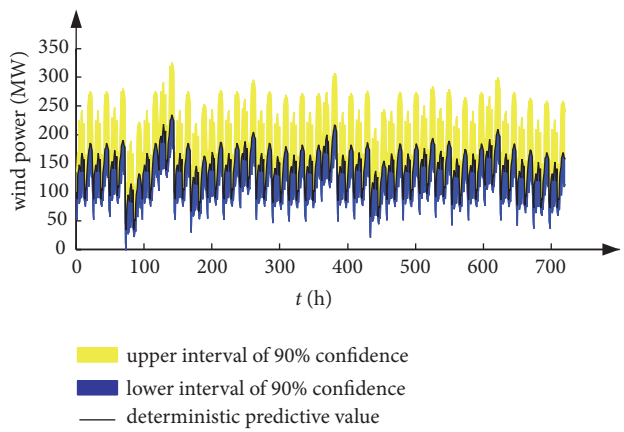

Figure 1: Monthly wind power output in 90% confidence interval.

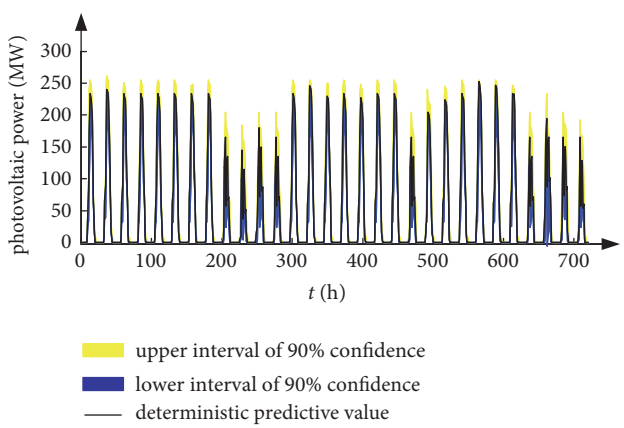

Figure 2: Monthly photovoltaic power output in 90% confidence interval.

3.1. Objective Function

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

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

$$F\left(P_{jt}\right) = a_j P_{jt}{}^2 + b_j P_{jt} + c_j \tag{2}$$

$$SC_{jt} = \begin{cases} C_j^{\text{hot}}, & T_j^{\text{off}} \le T_j^{\text{down}} + T_j^{\text{cold}} \\ C_j^{\text{cold}}, & T_j^{\text{off}} > T_j^{\text{down}} + T_j^{\text{cold}} \end{cases} \tag{3}$$

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 t time period; a_j, b_j, c_j are characteristic parameters of generation cost of unit j and they are all positive; C_j^{hot} and C_j^{cold} are hot and cold start cost; T_j^{off} is the continuous downtime of unit j; T_j^{down} is the minimum downtime of unit j; T_j^{cold} is the cold start time.

3.1.2. Optimization Goal 2: Reliability of the Power System. (1) Statistics of units start-off number

$$\beta = \sum_{t=1}^{T}\sum_{j=1}^{N}\left|X_j^t - X_j^{t-1}\right| \tag{4}$$

where X_j^t, X_j^{t-1} are the start-off status of the jth unit in the t and t-1 time period, respectively. If there is a change in start-off status, the index β is incremented by 1. Therefore, the smaller β is, the more reasonable the UC is, which avoids unnecessary switching.

(2) Margin of power supply

$$\alpha = \sum_{t=1}^{T} I\left(t\right)$$

$$I\left(\text{t}\right) = \begin{cases} 1, & \sum_{j=1}^{N} P_{jt}^{\text{r}} \bullet X_j^t < P_t^L \\ 0, & \sum_{j=1}^{N} P_{jt}^{\text{r}} \bullet X_j^t \ge P_t^L \end{cases} \tag{5}$$

where P_{jt}^{r} is the rated power of the thermal power unit j; P_t^L is the total load demand at time t. α is defined as the evaluation index that the total rated power of the system is greater than the 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 α 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:

$$R = \frac{\left(a\beta/N + b\alpha\right)}{T} \quad \left(a \ge 0,\ b \ge 0,\ a + b = 1\right) \tag{6}$$

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,...m) is normalized by (7) where x is the solution.

$$\varphi_e(x) = \frac{f_e(x) - f_{e,\min}}{f_{e,\max} - f_{e,\min}} \tag{7}$$

(2) Weights distribution of the objective function

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

$$u(f(x)) = \prod_{e=1}^{m} \varphi_e(x)^{r_e} \tag{8}$$

(3) Solving a single-objective function

$$\begin{aligned} &\min \quad \prod_{e=1}^{m} \varphi_e(x)^{r_e} \\ &s.t. \quad x \in X \end{aligned} \tag{9}$$

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:

$$\begin{aligned} \min \quad & CR = C_1(p)^{r_1} R_2(p)^{r_2} \\ & C_1(p) = \frac{C(p) - C_{\min}}{C_{\max} - C_{\min}} \\ & R_2(p) = \frac{R(p) - R_{\min}}{R_{\max} - R_{\min}} \\ \text{s.t.} \quad & p \in P \end{aligned} \tag{10}$$

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; $C_1(p)$, $R_2(p)$ 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 $R_2(p)$, respectively.

3.2. Constrains. (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).

$$\sum_{j=1}^{N} P_{jt}^{\max} + P_{Wt}^{\min} + P_{St}^{\min} - P_t^{R+} \geq P_t^L \tag{11}$$

$$\sum_{j=1}^{N} P_{jt}^{\min} + P_{Wt}^{\max} + P_{St}^{\max} + P_t^{R-} \leq P_t^L \tag{12}$$

where $P_{jt}^{\max}$, $P_{jt}^{\min}$ are the maximum and minimum active output of unit j during t time period; P_t^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_t^{R+}, P_t^{R-} are the positive and negative spinning reserves during t time period, respectively, and both of their values are the 10% of total load P_t^L during t time period.

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

$$\begin{aligned} T_j^{\text{on}} &\geq T_j^{\text{up}} \\ T_j^{\text{off}} &\geq T_j^{\text{down}} \end{aligned} \tag{13}$$

where T_j^{on}, T_j^{off} 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:

$$\sum_{j=1}^{N} P_{jt} + P_{Wt} + P_{St} = P_t^L \tag{14}$$

where P_{Wt}, P_{St} are the deterministic predictive values of wind power and photovoltaic power during t time period.

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

$$P_{jt}^{\min} \leq P_{jt} \leq P_{jt}^{\max} \tag{15}$$

where P_{jt} 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:

$$0 \leq P_{Wt} \leq P_{Wt}^r \tag{16}$$

where P_{Wt}^r is the rated wind power.

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

$$0 \leq P_{St} \leq P_{St}^r \tag{17}$$

where P_{St}^r 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:

$$\sum_{j\in\psi_c} P_{jt}^{\max} + P_{Wt}^{\max} + P_{St}^{\max} - P_t^L \le P_{ct} \tag{18}$$

where Ψ_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, 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.

$$S = \frac{\sum_{k=1}^{N\times T} f_k L_k}{\sum_{k=1}^{N\times T} f_k} \tag{19}$$

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

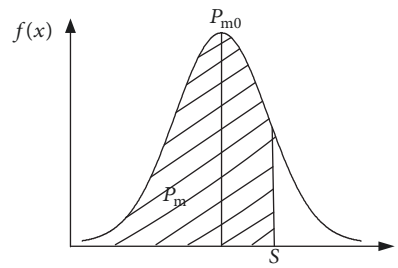

Figure 3: The relationship between P_m and S.

$$P_m = \int_{-\infty}^{S} f(x)\,dx$$
$$f(x) = \frac{1}{\sqrt{2\pi S}}\exp\left[-\frac{(x-P_{m0})^2}{2S}\right] \tag{20}$$

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. Both the capacities of positive and negative spinning reserves are 10% of the predicted total load. The interval prediction information of wind and photovoltaic power generation is shown in Figures 1 and 2, respectively. Aiming at the probable faults of units, the random number $\lambda(j)$ is compared with the forced failure rate $\mu(j)$ through random simulation. If $\lambda(j)\le\mu(j)$, the unit j is considered to be out of service; otherwise, it is considered to be in normal operation. The forced failure rates of each unit are shown in Table 1. 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.

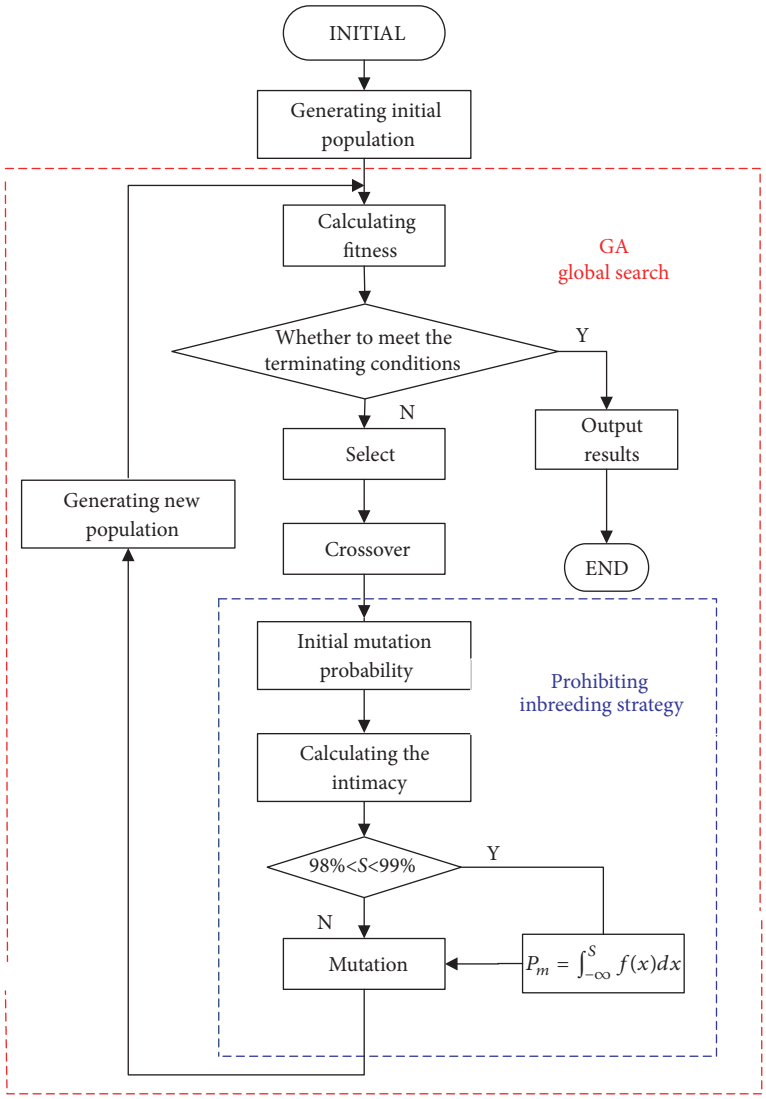

Figure 4: The flowchart of adaptive genetic algorithm.

Table 1: Forced failure rate of each unit.

unit	Forced failure rate	unit	Forced failure rate
1	0.0012	6	0.0012
2	0.0021	7	0.0021
3	0.0025	8	0.0025
4	0.0038	9	0.0038
5	0.0028	10	0.0028

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 × 107$ while that of the traditional GA is 1.5166 × 107$; 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 2: Results of weights assignment.

r_1	r_2	R	C	CR
0.2	0.8	0.0416	15566805	0.5034
0.4	0.6	0.0663	15334710	0.3799
0.5	0.5	0.0729	15149632	0.2596
0.6	0.4	0.0988	15080933	0.2584
0.8	0.2	0.1402	14969227	0.2279

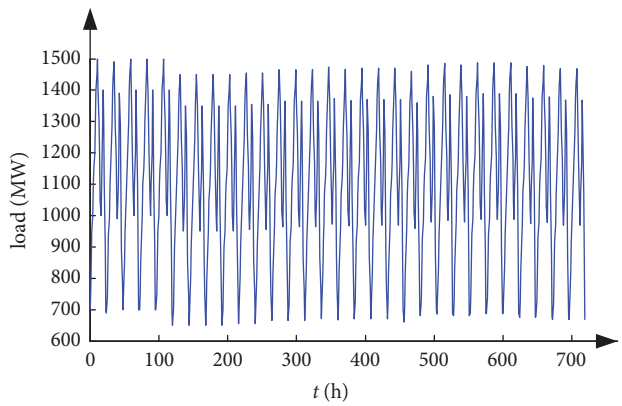

Figure 5: Hourly load.

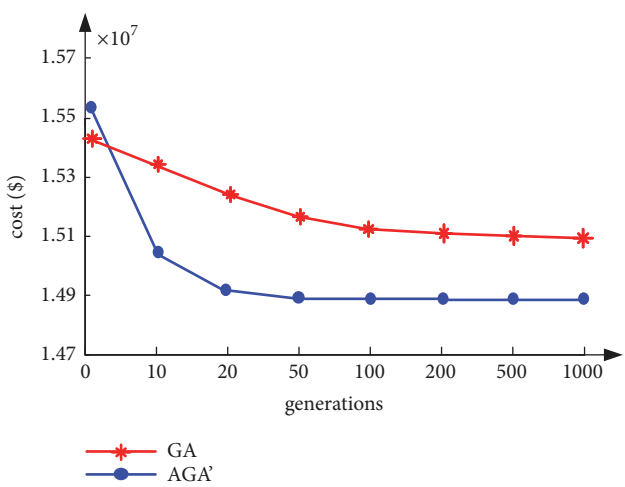

Figure 6: Convergence characteristics of traditional GA and AGA of the 10-unit system.

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.

Scale	Results	Algorithm		
		AGA	GA	BBO
10 units	optimal cost/10^7\$	1.5037	1.5106	1.5137
	worst cost/10^7\$	1.5525	1.5429	1.5525
	average cost/10^7\$	1.5290	1.5366	1.5390
	time/s	68	62	64
	reliable rate	0.0883	0.0985	0.0993
20 units	optimal cost/10^7\$	3.1003	3.1068	3.1163
	worst cost/10^7\$	3.2806	3.2907	3.2904
	average cost/10^7\$	3.2066	3.2512	3.2566
	time/s	138	136	148
	reliable rate	0.0916	0.1005	0.1016
40 units	optimal cost/10^7\$	6.3677	6.3881	6.36907
	worst cost/10^7\$	6.5470	6.5618	6.5660
	average cost/10^7\$	6.4681	6.4870	6.4088
	time/s	206	209	210
	reliable rate	0.0897	0.1102	0.1097
60 units	optimal cost/10^7\$	9.5410	9.5776	9.5561
	worst cost/10^7\$	9.7963	9.8064	9.7988
	average cost/10^7\$	9.6905	9.7173	9.7003
	time/s	289	367	328
	reliable rate	0.0812	0.0864	0.0822
80 units	optimal cost/10^7\$	12.833	12.908	12.862
	worst cost/10^7\$	13.345	13.679	13.447
	average cost/10^7\$	13.069	13.240	13.165
	time/s	363	488	420
	reliable rate	0.1069	0.1573	0.1307
100 units	optimal cost/10^7\$	16.017	16.099	16.087
	worst cost/10^7\$	16.320	16.414	16.339
	average cost/10^7\$	16.198	16.228	16.205
	time/s	493	692	583
	reliable rate	0.0993	0.1581	0.1229

Note: BBO is biogeography-based optimization algorithm.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This paper is supported by the National Natural Science Foundation of China (Grant no. 51677072).

References

[1] A. González, J.-R. Riba, A. Rius et al., "Optimal sizing of a hybrid grid-connected photovoltaic and wind power system," *Applied Energy*, vol. 154, pp. 752–762, 2015.

[2] Q. Xia, Y. Chen, and L. Chen, "Establishment of mode and method for energy-conservation monthly unit commitment considering dispatching," *Dianwang Jishu/Power System Technology*, vol. 35, no. 6, pp. 27–33, 2011.

[3] Z. W. Zheng, Y. Y. Chen, M. M. Huo et al., "An overview: the development of prediction technology of wind and photovoltaic power generation," *Energy Procedia*, vol. 12, no. 12, pp. 601–608, 2011.

[4] J. Liu, W. Fang, X. Zhang et al., "An improved photovoltaic power forecasting model with the assistan- ce of aerosol andex data," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 2, pp. 434–442, 2015.

[5] A. Botterud, Z. Zhou, J. Wang et al., "Demand dispatch and probabilistic wind power forecasting in unit commitment and economic dispatch: a case study of illinois," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 250–261, 2013.

[6] M. Govardhan and R. Roy, "Comparative analysis of economic viability with distributed energy resources on unit commitment," *Electric Power Components and Systems*, vol. 44, no. 14, pp. 1588–1607, 2016.

[7] H. Hashimoto, H. Hirano, K. Hirose et al., "Long-term generation scheduling method with constrained numbers of unit commitment and fuel constraints on thermal units," *Electrical Engineering in Japan (English translation of Denki Gakkai Ronbunshi)*, vol. 187, no. 4, pp. 18–28, 2014.

[8] Y. Guo, H. Kuang, S. Guo et al., "Research on weekly unit commitment strategy harmonizing long term market trade planning anddaily generation scheduling," *Power System Protection and Control*, vol. 45, no. 22, pp. 78–82, 2017.

[9] C. De Jonghe, B. F. Hobbs, and R. Belmans, "Value of price responsive load for wind integration in unit commitment," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 675–685, 2014.

[10] N. Zhang, Z. Hu, D. Dai et al., "Unit commitment model in smart grid environment considering carbon emissions trading," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 420–427, 2016.

[11] F. Aminifar, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Unit commitment with probabilistic spinning reserve and interruptible load considerations," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 388–397, 2009.

[12] J. Van Dinter, S. Rebennack, J. Kallrath, P. Denholm, and A. Newman, "The unit commitment model with concave emissions costs: a hybrid Benders' decomposition with nonconvex master problems," *Annals of Operations Research*, vol. 210, no. 1, pp. 361–386, 2013.

[13] E. Delarue, D. Cattrysse, and W. D'haeseleer, "Enhanced priority list unit commitment method for power systems with a high share of renewables," *Electric Power Systems Research*, vol. 105, no. 6, pp. 115–123, 2013.

[14] W. L. Snyder, H. D. Powell, and J. C. Rayburn, "Dynamic programming approach to unit commitment," *IEEE Transactions on Power Systems*, vol. 2, no. 2, pp. 339–348, 2007.

[15] D. Murata and S. Yamashiro, "Unit commitment scheduling by lagrange relaxation method taking into account transmission losses," *Electrical Engineering in Japan (English translation of Denki Gakkai Ronbunshi)*, vol. 152, no. 4, pp. 27–33, 2005.

[16] S. Chakraborty, T. Ito, T. Senjyu, and A. Y. Saber, "Unit commitment strategy of thermal generators by using advanced fuzzy controlled binary particle swarm optimization algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 1072–1080, 2012.

[17] D. Datta, "Unit commitment problem with ramp rate constraint using a binary-real-coded genetic algorithm," *Applied Soft Computing*, vol. 13, no. 9, pp. 3873–3883, 2013.

[18] D. Li, Z. Ren, W. Yan et al., "Month-ahead wind power curve probabilistic prediction based on factor analysis and quantile regression neural network," *Proceedings of the Csee*, vol. 37, no. 18, pp. 5238–5247, 2017.

[19] J. I. Peláez, J. M. Doña, and A. Mesas, "Majority multiplicative ordered weighting geometric operators and their use in the aggregation of multiplicative preference relations," *Mathware & Soft Computing*, vol. 12, no. 2-3, pp. 107–120, 2007.

[20] S. Frank and S. Rebennack, "An introduction to optimal power flow: theory, formulation, and examples," *IIE Transactions*, vol. 48, no. 12, pp. 1172–1197, 2016.

[21] S. Khanmohammadi, M. Amiri, and M. T. Haque, "A new three-stage method for solving unit commitment problem," *Energy*, vol. 35, no. 7, pp. 3072–3080, 2010.

[22] D. Chen, Q. Gong, H. Qiao et al., "Multi-objective generation dispatching for wind power integrated system adopting improved biogeography-based optimization algorithm," *Proceedings of the Csee*, vol. 32, no. 31, pp. 150–158, 2012.