Improved Binary Artificial Fish Swarm Algorithm and Fast Constraint Processing for Large Scale Unit Commitment

YONGLI ZHU, (Member, IEEE), AND HUI GAO

School of Electrical and Electronic Engineering, North China Electric Power University, Baoding 071003, China

Corresponding author: Yongli Zhu (yonglipw@163.com)

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ABSTRACT As the power systems in some large developing and developed countries are getting bigger, solving large-scale unit commitment (UC) is an urgent need and significant task to ensure their economic operation and contribute green energy consummation to society. In this article optimization models covering economy and environmental protection are established, and an improved binary artificial fish swarm algorithm (IBAFSA) is presented to solve the large-scale UC problems. The parameters of IBAFSA are improved by Lévy flight and adaptive average visual distance to search space more actively, and a double threshold selection strategy is used to enhance the effectiveness of population evolution in the optimization. Meanwhile, a heuristic greedy search algorithm among the best individuals of all generations in the iterative process of the optimization is proposed, which is beneficial to improve computation convergence and reach the optimum solution. A fast constraints processing mechanism based on the heuristic modifying strategy of unit violation is established to handle the coupling between system spinning reserve constraint and unit minimum up and down time constraint. The effectiveness of the proposed approach is verified by the UC simulations of test systems of 10-1000 units, the IEEE 118-bus system, and a large-scale power system of 270 units. The numerical simulating results show that the proposed UC solution method can achieve the near-optimal solutions in a reasonable time, improve the economic and environmental benefits of a large-scale power system, and is a general method to adapt to the changes of the objective function and constraints of a UC optimization.

INDEX TERMS Large-scale unit commitment, improved binary artificial fish swarm algorithm, heuristic greedy search, UC fast processing mechanism for constraint, environmental economic dispatch.

NOMENCLATURE

- \( T \): Number of scheduling hours
- \( N \): Number of thermal units
- \( t \): Index for time intervals (\( t = 1, 2, \cdots T \))
- \( i \): Index for thermal units (\( i = 1, 2, \cdots N \))
- \( F(P_t^i) \): Fuel cost of unit \( i \) at hour \( t \)
- \( E(P_t^i) \): Pollutant gas emission of the unit \( i \) at hour \( t \)
- \( u_t^i \): Status of the unit \( i \) at hour \( t \) (“1” → on, “0” → off)
- \( P_t^i \): Output power of unit \( i \) at hour \( t \)
- \( P_{i,\text{max}}^t, P_{i,\text{min}}^t \): Maximum and Minimum generation limit of unit \( i \)
- \( U_{R_t}, D_{R_t} \): Ramp-up and ramp-down limit of unit \( i \)
- \( C_{S_t}^i, C_{D_t}^i \): Start-up and shut-down costs of unit \( i \)
- \( C_{S_t}^i, C_{H_t}^i \): Cold and hot start-up cost of unit \( i \)
- \( M_{D_t}, M_{U_t} \): Minimal uptime and downtime of unit \( i \)
- \( T_{i,\text{on}}, T_{i,\text{off}}^t \): Continuously on and off time of unit \( i \) till time \( t \) in hours
- \( T_{\text{cold}}^i \): Cold start-up time of unit \( i \)
- \( P_{d}^t \): System load demand at hour \( t \)
- \( S_{R}^t \): System spinning reserve at hour \( t \)
- \( X_{t}^{g+1} \): The updated position of artificial fish \( i \)

I. INTRODUCTION

Unit commitment (UC) is important to power system scheduling and operation. It is a complicated optimization decision-making process that is coupled with the on/off schedule of generating units and the optimal output [1], [2]. With the power systems in some large countries such as China, USA...
and India getting larger and larger, and much attention being paid to the problem of air pollution, solving large-scale UC is an urgent need and significant task to electric utilities. However, at present solving large-scale UC problems of the large power systems is challenging both to the utilities and the researchers in this field [3].

The UC problem is a non-convex, high-dimensional mixed-integer and non-linear programming model in mathematics, which is difficult to directly reach a theoretical optimal solution [2]. Besides, the number of unit 0-1 variables is increased exponentially, and the constraints become more complicated with the expansion of power system size. So far, the priority list method (PL) [4], dynamic programming (DP) [5], Lagrangian relaxation algorithm (LR) [6], mixed-integer linear programming (MILP) [7], [8], and various artificial intelligence optimization algorithms have been applied to the UC problem, but these solutions have the following limitations. The PL is simple to implement, but its solution effect depends on human experience and it is difficult to get an optimal solution. The DP exhausts all possible unit commitments, while it is prone to fall into dimensional disaster with the increasing number of generating units. The LR can simplify the dimension of UC, but it has the dual gap problem and can not effectively deal with large-scale constraints. The MILP generally approximates UC as a mixed-integer linear programming problem, which can acquire the optimal solution with high quality in theory, whereas it has the defects of a large amount of calculation and slow convergence solving the large-scale UC problem [9].

To solve the large-scale UC problem, some intelligent optimization algorithms such as binary particle swarm optimization (BPSO) [10], hybrid harmony search/random algorithm (HHSR) [11], differential evolution algorithm (DE) [12], and grey wolf optimizer (GWO) [13] have appeared. These algorithms can use a penalty function method or repair strategy to handle nonlinear constraints in the problem. However, they are affected by parameter settings and easy to fall into a local minima value. Moreover, the large-scale UC is a high-dimensional optimization with equality and inequality constraints. Thus, improving the existing optimization approaches and exploring fast constraint processing techniques are very important to effectively solve the UC problem.

A two-level hierarchical approach that combines an expert system (ES) with an elite particle swarm optimization (IBAFSA) is presented to implement the coupling problem of constraints. The IBAFSA algorithm is proposed to find the global optimal solution, which is suitable for solving high-dimensional optimization [19], [20]. In recent years, it has been successfully applied in the fields of Data Mining, Signal Processing and Communication, etc [21]–[23], but has quite few applications in the UC problem. Meanwhile, it also has the drawback of falling into local optimum. Due to the diversity of fish behavior in the optimization process, it has high time complexity. Therefore, the authors try to find a new fish behavior selection strategy to update the population effectively and quickly.

As environmental pollution and global warming have become increasingly serious in recent years, many countries have begun to enforce the policy of energy-saving and emission reduction. Hence large-scale UC models should also consider the environmental cost of generation to maximize social benefits [24]. Meanwhile, existing UC studies mainly concern to small and medium-scale systems (100 units and below), and few can conduct the UC for hundreds of generating units.

To cope with the problems mentioned above, this article establishes UC optimization models considering both the operating and environmental costs of the units and proposes a solution method for a large-scale UC. Specifically, because AFSA also has the drawback of falling into local optimum, an improved binary artificial fish swarm algorithm (IBAFSA) is proposed to improve the convergence and global optimization performance in the large-scale UC. Moreover, for the fast solution requirement of the large-scale UC problem, the fast constraints processing mechanism is presented to handle the coupling problem of constraints. The main contributions of this article are summarized as follows.

- The IBAFSA algorithm is presented to implement the large-scale UC models. The parameters of algorithm are improved by the Lévy flights and adaptive average visual distance to more actively search space. A double threshold selection strategy is used to enhance the effectiveness of population evolution. Compared with other intelligent optimization algorithms, the proposed one has good global optimization performance and can obtain higher quality near-optimal solution.
- Considering the influence of unit output on the UC priority list, a heuristic greedy search algorithm is proposed to find the global optimal solution, which is
beneficial to improve computation convergence and reach an optimal solution.

- To cope with the coupling between system spinning reserve constraint and unit minimum up and down time constraint, a fast constraint processing technique based on a heuristic modification strategy is proposed to solve unit violations in the scheduling process. It can efficiently handle the large-scale constraints to reduce the UC solution time.

The rest of this article is organized as follows: Section II provides the UC problem formulation. Section III presents the specific improvement measures of BAFSA. The UC constraint fast processing mechanism and the solution procedures of the UC model are proposed in Section IV. The numerical tests are analyzed in Section V and the conclusions are arranged in Section VI.

II. UC PROBLEM FORMULATION

The essence of UC is a total cost minimization problem to determine the optimal on/off status and output scheduling of the units in a power system over a scheduling period based on the forecasted load curve and the unit data while satisfying system constraints and unit constraints. As environmental pollution and global warming are becoming more serious, the environmental cost should also be taken into UC models. Therefore, the solution method should be general to adapt to the changes of constraints and objective functions of a UC problem. As the power systems of some countries are getting larger, finding the method to solve large-scale UC problems is necessary.

A. OBJECTIVE FUNCTION

The conventional UC problem focuses on system operating costs, which is modeled as a minimization problem of total operating cost (TOC) that constitutes of fuel cost, start-up and shut-down costs in (1).

\[
TOC = \sum_{i=1}^{N} \sum_{t=1}^{T} [(F(P_i^t) + h(t)E(P_i^t))u_i^t + CS_i(1 - u_i^t)^{-1}(1 - u_i^t)]
\]

where \(F(P_i^t) = a_i(P_i^t)^2 + b_i(P_i^t) + c_i\) (2)

The fuel cost of generators is formulated by a quadratic polynomial function of the unit output in (2).

The shut-down cost is generally considered as a constant and is ignored in this article. The thermal unit start-up cost depends on the unit previously off-line time, which is given by (3).

\[
CS_i = \begin{cases} CSH_i, & MDT_i \leq T_i^{off} \leq MDT_i + T_i^{cold} \\ CSC_i, & T_i^{off} \geq MDT_i + T_i^{cold} \end{cases}
\]

However, with the policy of energy-saving and emission reduction being enforced, the environmental cost (EC) quantified by the pollutant gas emissions of thermal power units is introduced to the UC. Thus the objective of the UC is formulated as

\[
\min \sum_{i=1}^{N} \sum_{t=1}^{T} [(F(P_i^t) + h(t)E(P_i^t))u_i^t + CS_i(1 - u_i^t)^{-1}(1 - u_i^t)]
\]

where \(h(t)\) is the price penalty factor for pollutants at time \(t\) [25]; the pollutant gas emissions \(E(P_i^t)\) are calculated by a quadratic polynomial function in (5).

\[
E(P_i^t) = \alpha_i(P_i^t)^2 + \beta_i(P_i^t) + \gamma_i
\]

where \(\alpha_i, \beta_i,\) and \(\gamma_i\) are the pollutant emission parameters of the unit;

B. CONSTRAINTS

1) POWER SYSTEM BALANCE CONSTRAINT

The total generation of all the committed units at each hour of the scheduled time period must satisfy the load demand.

\[
\sum_{i=1}^{N} u_i^t P_i^t - P_d = 0
\]

2) SYSTEM SPINNING RESERVE CONSTRAINT

To ensure the reliability of system operation, sufficient spinning reserves are required as (7) which can be specified in terms of excess generation output.

\[
\sum_{i=1}^{N} u_i^t(P_i^{max} - P_i^t) \geq SR
\]

3) RAMP RATE CONSTRAINT

The adjustable range of online units in adjacent periods is constrained by the up and down ramp rate.

\[
\begin{align*}
P_i^t - P_i^{t-1} &\leq UR_i \\
P_i^{t-1} - P_i^t &\leq DR_i
\end{align*}
\]

4) UNIT GENERATION LIMIT CONSTRAINT

The minimum and maximum power generation capacity of each online unit is constrained as

\[
P_i^{min} \leq P_i^t \leq P_i^{max}
\]

5) MINIMUM UP AND DOWN TIME CONSTRAINT

A unit must remain on/off for a period of time when it is committed / de-committed.

\[
\begin{align*}
(T_i^{on} - MUT_i)(u_i^{t-1} - u_i^t) &\geq 0 \\
(T_i^{off} - MDT_i)(u_i^t - u_i^{t-1}) &\geq 0
\end{align*}
\]

III. IBAFSA FOR SOLVING UC

A. BRIEF REVIEW OF BAFSA

AFSA follows the top-down optimization that imitates the searching, clustering, chasing, and random behavior of fish in nature to achieve global optimum. It selects the searching behavior by comparing the food consistency and the factor of congestion within the visual distance, which causes the
calculation speed is slower solving the high-dimensional optimization problems. Moreover, the implementation of clustering behavior requires to find the center of artificial fish, which also reduces the efficiency of BAFSA. In this article, we consider the searching, chasing, and random behavior of fish for solving UC [26].

Inspired by the binary grey wolf optimization algorithm [13], the probabilities $r_1$ and $r_2$ are introduced in this article with $0 \leq r_1 \leq r_2 \leq 1$. The swarm is updated quickly and effectively by (11).

$$X_{g+1}^i = \begin{cases} X_{r,i}^{g+1}, & 0 \leq r \leq r_1 \\ X_{p,i}^{g+1}, & r_1 \leq r \leq r_2 \\ X_{c,i}^{g+1}, & r_2 \leq r \leq 1 \end{cases}$$

(11)

where $X_{r,i}^{g+1}$, $X_{p,i}^{g+1}$, and $X_{c,i}^{g+1}$ refer to the position of the fish $i$ after the random, searching, and chasing behavior is performed respectively; $r$ is a random number between 0-1.

Since Eq. (11) is implemented based on the real coding, the updated fish swarm is mapped to the discrete space by (12) and (13).

$$f(X_{g}^{i+1}) = \frac{\exp(2 \times |X_{g}^{i+1}|) - 1}{\exp(2 \times |X_{g}^{i+1}|) + 1}$$

(12)

$$X_{g}^{i+1} = \begin{cases} 1, & f(X_{g}^{i+1}) \geq \tau \\ 0, & \text{otherwise} \end{cases}$$

(13)

where $\tau$ is a random number between 0-1.

### B. THE IMPROVEMENT OF BAFSA

BAFSA is a swarm intelligent optimization algorithm with good global optimization and convergence performance. However, it still has the shortcomings of easy to fall into local optimization solving large-scale UC with complex constraints. In this research, its original parameters are improved to enhance its optimization performance and a new binary selection strategy is adopted to enhance the effectiveness of its population evolution. To improve the convergence of the optimization, a heuristic greedy search is also proposed. The specific improvement measures are stated as follows.

1) PARAMETER UPDATES BASED ON LÉVY FLIGHTS AND ADAPTIVE AVERAGE VISUAL DISTANCE

In the classical BAFSA, Step and Visual are the random parameter or parameter that changes adaptively with the number of iterations. Random parameter can expand the scope of optimization, but it slows down the convergence speed. While the parameter changing with the number of iterations is opposite to the former, which sacrifices the ability of global search to some extent and is easy to fall into local optimization. To enhance the optimization and convergence performance of BAFSA, Lévy flight step and adaptive average visual distance are adopted to improve the algorithm parameters in this article.

Lévy flight is a random walk step that simulates the behavior of animals or insects. It can search randomly and alternately with uninterrupted short jumps and occasionally long steps, which is an essential method to describe the Lévy distribution [27], [28]. It has the characteristics of increasing population diversity and expanding search space, so the global optimization ability of algorithm can be improved by replacing the original step parameter. Lévy flight step is represented in (14).

$$\begin{cases} \text{Step} = \text{Step}_{\max} \cdot \text{ levy}() \\ \text{ levy}() = 0.01 \times \frac{\mu}{|v|^{1/\beta}} \end{cases}$$

(14)

where $\text{Step}_{\max}$ is the maximum moving step; $\text{ levy}()$ is the Lévy flight step; $\mu \sim N(0, \sigma_{\mu}^2)$, $\nu \sim N(0, 1)$, and $\sigma_{\mu}$ is represented as

$$\sigma_{\mu} = \left\{ \begin{aligned} \Gamma(1 + \beta) \sin(\pi \beta / 2) \\ \Gamma[(1 + \beta) / 2] \beta 2^{(\beta - 1)/2} \end{aligned} \right\}^{1/\beta}$$

(15)

where $\Gamma$ is the gamma function; $\beta$ is $(0, 2)$, which is set as a constant 1.5 in this article.

The adaptive average visual distance (Visual) of artificial fish is determined by the average of the distances from other artificial fish to itself. At the initial of optimization, artificial fishes are randomly distributed in the feasible region, and they are far away from each other, that is, Visual is large in the initial, which can effectively overcome the influence of local extreme values. As the swarm of fish continues to gather, it decreases adaptively among artificial fishes, thereby improving the search efficiency of artificial fish. It is expressed by (16).

$$A_{\text{Visual}}^i = \sum_{j=1, j \neq i}^{\text{pop}} D_{i,j}^g / (\text{pop} - 1)$$

(16)

where $A_{\text{Visual}}^i$ is the average visual distance of artificial fish $i$ at the $g$-th iteration.

2) DOUBLE THRESHOLD SELECTION STRATEGY

In the binary intelligent algorithm, the population is mapped from continuous space to the discrete by Eq. (12) and Eq. (13). However, the transformation results generally depend on the random number $\tau$. If $\tau$ is too small, the individual tends to choose 1, otherwise 0, which weakens the effectiveness of fish evolution. Fig. 1 shows the cumulative probability distribution of 1000 random numbers generated by the uniform distribution. It can be seen from the figure that the proportion of random numbers between 0.1 and 0.9 reaches 80%.

According to the above phenomena, a binary conversion strategy based on double threshold selection is defined as

$$X_{g}^{i+1} = \begin{cases} 1, & f(X_{g}^{i+1}) \geq \tau_1, \tau_1 \leq \tau \leq \tau_2 \\ 0, & \text{otherwise} \end{cases}$$

(17)

where $\tau_1$ and $\tau_2$ are the random thresholds of $\tau$. 
Most researchers solve the coupling problem by handling the some units to violate their up and down time constraints. and the repair of the spinning reserve constraint may cause a set of mutually coupled constraints. For example, repair- ing unit minimum up and down time constraints may lead a set of mutually coupled constraints. For example, repair- ing unit minimum up and down time constraints may lead to the violation of the system spinning reserve constraint; and the repair of the spinning reserve constraint may cause some units to violate their up and down time constraints. Most researchers solve the coupling problem by handling the

3) HEURISTIC GREEDY SEARCH IN IBAFSA

The intelligent algorithm can converge to a near-optimal solution stably by executing the optimization strategy. Whereas, with the complexity of the optimization problem, the increasing number of variables usually causes the solution falling into local optimum, a fatal weakness for large-scale UC problems. The existing research often uses the average fuel cost of full load to determine the unit priority list, that is, the unit with low cost is more economical than the high. However, there is exactly the opposite when the unit is forced to start with the low output. Hence the heuristic local search algorithm based on the minimum unit output priority is proposed to modify the global optimal unit state, which adopts the greedy update evaluation strategy. In the greedy optimal process, only the update values that improve the current solution can be accepted. The strategy can ensure the optimal solution of each generation is used to guide the local search in the evolution process to obtain a higher quality solution and increase the convergence of the optimization. Algorithm 1 shows the pseudo-code of the heuristic greedy search.

IV. PROPOSED SOLUTION METHODOLOGY

The efficiency of solving the UC problem is also influenced by the constraint processing technique. A fast constraint handling mechanism based on the unit violations is developed to solve the coupling problem of UC constraints. Fig. 2 is the flow chart of the UC constraint processing mechanism.

A. UC FAST PROCESSING MECHANISM FOR CONSTRAINTS

In the UC problem, unit 0-1 decision needs to satisfy unit minimum up and down time constraint and system spinning reserve constraint at the same time. In fact, they are a set of mutually coupled constraints. For example, repairing unit minimum up and down time constraints may lead to the violation of the system spinning reserve constraint; and the repair of the spinning reserve constraint may cause some units to violate their up and down time constraints. Most researchers solve the coupling problem by handling the

Algorithm 1 Heuristic greedy search

1: //AFC\textsubscript{min}: average fuel cost of each unit with its minimum output
2: //PL\textsubscript{m}: priority list of units based AFC\textsubscript{min}
3: //gbest: global optimal unit status
4: Function HGS(N, T, AFC\textsubscript{min}, PL\textsubscript{m}, gbest)
5: Begin
6: gbest\textsubscript{new} = gbest
7: t ← \text{rand}(1, T);
8: M ← start-up unit of gbest at time t
9: l ← calculate the number of units in M
10: For i = 1 : l
11: \quad If L == N
12: \quad \quad break
13: End If
14: p ← PL\textsubscript{m}(M(i))
15: If p == N
16: \quad break
17: End If
18: If AFC\textsubscript{min} (p + 1) == AFC\textsubscript{min} (p) &&
19: \quad gbest\textsubscript{new}(PL\textsubscript{m}(p + 1), t) == 0
20: \quad gbest\textsubscript{new}(M(i)) = 0
21: \quad gbest\textsubscript{new}(PL\textsubscript{m}(p + 1), t) = 1
22: End If
23: End For
24: Constraints repair for gbest\textsubscript{new}
25: If f(gbest\textsubscript{new}) < f(gbest)
26: \quad gbest = gbest\textsubscript{new}
27: End If
28: Return gbest
29: End
Meanwhile, the number and location of the violation items are used to describe the violation characteristics of the statuses of a unit in all scheduling period (24 hours) which cause constraint violation. The number of unit violation items refers to the number of violation slots in the 24 hours, and the location means the beginning hour and end hour of a violation time slot.

In the proposed heuristic modifying strategy, the information of unit violation is used to repair \( \text{Cur}_u \) for satisfying minimum up and down time constraints. The contents of the strategy include the following.

1) UNIT STATUS PRE-PROCESSING
If there are units of off status in the unit violation item, they are repaired to on status to improve the efficiency of processing unit minimum up and down time constraints.

2) PERFORMING THE HEURISTIC MODIFYING STRATEGY BASED ON THE NUMBER OF UNIT VIOLATIONS
There are two rules to perform the modification of the violation statuses which are based on the number and location of violation items.

**Rule A)** Repair strategy for a single violation item
If a unit has a single violation item in the scheduling period (24 hours) and its committed hour number before or after the violation item reaches to its minimum up hour number, its statuses at another time side of the item are repaired, changed, to satisfy its minimum up and down time constraint. Fig. 3 demonstrates the repairing process under the above situation with the upper part representing the pre-repaired statuses of an MDT violated unit in 24 hours, and the lower indicating its repaired statuses. In the figure, I.S means the number of running hours of the unit before making the UC schedule. If its statuses at both sides of a violation item are de-committed or are committed not reaching to its minimum up hour number, unit statuses at one side of the violation item are selected and changed to satisfy the unit minimum up and down time range randomly.

**Rule B)** Repair strategy for multiple unit violation items
If a unit has multiple violation items in the scheduling period, only the location of the first violation item that belongs to the earliest violation hours of the scheduling period is determined initially. Then, the statuses of the unit before the violation item are changed to satisfy its minimum up and down time range, and its initial status. In the end, its statuses in the following hours of the item, throughout the last hour of the scheduling period, are repaired to satisfy its minimum up and down time constraint. Fig. 4 illustrates the repairing process under the above situation with the upper part representing the pre-repaired statuses including two violation items in 24 hours, and lower part indicating its repaired statuses.

**B. PROCEDURE OF SOLVING UC**

1) Set IBAFSA parameters and initialize on/off status of all units in several ways to form population \( U \);
2) Generate a feasible solution \( U_F \) based on the fast UC constraint processing mechanism stated in Section IV-A to satisfy the unit minimum up and down time constraints and spinning reserve constraint;
3) Based on the feasible solution \( U_F \) determined in step 2), \( \lambda \) iteration method is adopted to optimize the UC schedule;
4) Calculate the fitness of objective function according to Eq. (1) or Eq. (4), and save the current optimal fitness and on/off schedule of all units;
5) Use heuristic greedy search to get a better schedule based on the schedule obtained at step 4);
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TABLE 1. Generating unit data for the 10-unit system.

| Parameter | Unit 1 | Unit 2 | Unit 3 | Unit 4 | Unit 5 | Unit 6 | Unit 7 | Unit 8 | Unit 9 | Unit 10 |
|-----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| $p^\text{min}$ | 455 | 455 | 130 | 130 | 162 | 80 | 85 | 55 | 55 | 55 |
| $p^\text{max}$ | 150 | 150 | 20 | 20 | 25 | 20 | 25 | 10 | 10 | 10 |
| $a_i$ | 0.00048 | 0.00031 | 0.002 | 0.00211 | 0.00398 | 0.00712 | 0.00079 | 0.00413 | 0.00222 | 0.00173 |
| $b_i$ | 16.19 | 17.26 | 16.6 | 16.5 | 19.7 | 22.26 | 27.74 | 25.92 | 27.27 | 27.79 |
| $c_i$ | 1000 | 970 | 700 | 680 | 450 | 370 | 480 | 660 | 665 | 670 |
| $\alpha_i$ | 0.0312 | 0.0312 | 0.0509 | 0.0509 | 0.0344 | 0.0344 | 0.0465 | 0.0465 | 0.0470 | 0.0470 |
| $\beta_i$ | -2.4444 | -2.4444 | -4.0695 | -4.0695 | -3.8132 | -3.8132 | -3.9023 | -3.9023 | -3.9524 | -3.9864 |
| $\gamma_i$ | 103.3908 | 103.3908 | 300.3910 | 300.3910 | 320.0006 | 320.0006 | 330.0056 | 330.0056 | 350.0056 | 360.0012 |
| $\text{CSH}_i$ | 4500 | 5000 | 550 | 560 | 900 | 170 | 260 | 30 | 30 | 30 |
| $\text{CSC}_i$ | 9000 | 10000 | 1100 | 1120 | 1800 | 340 | 520 | 60 | 60 | 60 |
| $T_i^\text{wind}$ | 5 | 5 | 4 | 4 | 4 | 2 | 2 | 0 | 0 | 0 |
| $\text{MUT}_i$ | 8 | 8 | 5 | 5 | 6 | 3 | 3 | 1 | 1 | 1 |
| $\text{MDT}_i$ | 8 | 8 | 5 | 5 | 6 | 3 | 3 | 1 | 1 | 1 |
| $\text{LS}_i$ | 8 | 8 | -5 | -5 | -5 | -6 | -3 | -3 | -1 | -1 |

6) Judge whether the error between the current function values and that of last iteration. If so, go to step 9); otherwise go to step 7);

7) Select a kind of artificial fish swarm behavior to update the population based on Eq. (11), and map it to the discrete space using Eq. (12) and Eq. (17);

8) Go back to step 2) and carry out the above loop steps;

9) Output the optimal unit on/off schedule, output, etc.

V. SIMULATION AND ANALYSIS

The proposed approach is implemented in Matlab 2017b on a PC with Intel Core i5 of 2.5 GHz and 8 GB RAM. Several cases which include 10- to 1000-unit test systems, IEEE 118-bus system with 54 thermal units, and a large-scale power system with 270 thermal units are tested using the proposed method. The system spinning reserve requirement is assumed to be 10% of the hourly load demand [10], [12].

A. PARAMETER SETTING OF IBAFSA

The maximum moving step length of an artificial fish adopted by IBAFSA is set to 5. The error between the current function values and that of last iteration is used as its termination condition, which is set to $10^{-6}$. The probabilities $r_1$ and $r_2$ in Eq. (11) are 0.3 and 0.7, respectively. The optimization performance of IBAFSA is not sensitive to the size of the population ($pop$), and the optimal value can be obtained when the $pop$ is set to 20, which is proved by the testing results shown in Table 2. In this research, the $pop$ of the system with no more than 100 units is set as 20, and that of more than 100 units is set as 40.

B. 10 to 1000-UNIT TEST SYSTEM

The power systems with 10, 20, 40, 60, 80, 100, 200, 800, and 1000 units are respectively tested to demonstrate the efficiency of the proposed method. All the data of the larger test systems are made by duplicating that of the 10-unit system and scaling the load demand in proportion to the size of the 10-unit system. The data of the 10-unit system are taken from [29] and presented in Table 1.

The optimal results obtained by running any intelligent optimization algorithm are random to some degree. In this article, the best results from 20 independent runs are taken as the final optimal solutions. Table 2 shows the results for 20- and 100-unit UC problems. It can be seen that the optimal UC results become a little bit better with the increase of the size population ($pop$), and the average operating cost decreases gradually and tends to be consistent. Meanwhile, the UC solution time gets linear growth with the increase of $pop$. From Table 2, the optimal result of the 20-unit UC problem can be obtained when $pop$ is 10. The worst and the average costs decrease slightly with the increase of $pop$.

1) COMPARISON OF IBAFSA WITH STANDARD BAFSA

To verify the advantages of the proposed approach over the standard BAFSA in solving UC problems, the UC of 10-, 20-, 40-, 60-, and 100-unit systems are tested and the results are listed in Table 3. In the table, the best costs, worst costs, mean costs, standard deviation, and execution time for the test systems by the proposed method are compared with

| # of units | Best cost/\$ | Worst cost/\$ | Mean cost/\$ | Standard deviation | Mean time/s |
|-----------|-------------|--------------|-------------|--------------------|-------------|
| 10 | 1123297 | 1124336 | 1123893 | 366 | 6.9 |
| 20 | 1123297 | 1124305 | 1123855 | 395 | 10.7 |
| 40 | 1123297 | 1124305 | 1123940 | 405 | 20.1 |
| 60 | 1123297 | 1124274 | 1123960 | 380 | 31.4 |
| 100 | 5609026 | 5611678 | 5610532 | 950 | 37.7 |
| 20 | 5607516 | 5610210 | 5608698 | 1010 | 76.1 |
| 40 | 5607516 | 5609559 | 5608693 | 1002 | 147.8 |
| 60 | 5607516 | 5609527 | 5608169 | 1034 | 215.1 |

The optimal results obtained by running any intelligent optimization algorithm are random to some degree. In this article, the best results from 20 independent runs are taken as the final optimal solutions. Table 2 shows the results for 20- and 100-unit UC problems. It can be seen that the optimal UC results become a little bit better with the increase of the size population ($pop$), and the average operating cost decreases gradually and tends to be consistent. Meanwhile, the UC solution time gets linear growth with the increase of $pop$. From Table 2, the optimal result of the 20-unit UC problem can be obtained when $pop$ is 10. The worst and the average costs decrease slightly with the increase of $pop$.

1) COMPARISON OF IBAFSA WITH STANDARD BAFSA

To verify the advantages of the proposed approach over the standard BAFSA in solving UC problems, the UC of 10-, 20-, 40-, 60-, and 100-unit systems are tested and the results are listed in Table 3. In the table, the best costs, worst costs, mean costs, standard deviation, and execution time for the test systems by the proposed method are compared with
TABLE 3. Performance comparison of IBAFSA and BAFSA.

| # of units | Method | Best/$ | Worst/$ | Mean/$ | Std% | Time/s |
|------------|--------|--------|--------|--------|------|--------|
| 10         | BAFSA  | 563977 | 564848 | 564131 | 0.15 | 7.6    |
|            | IBAFSA | 563938 | 563938 | 563938 | 0.00 | 4.2    |
| 20         | BAFSA  | 1124099| 1125336| 1124536| 0.11 | 11.5   |
|            | IBAFSA | 1123297| 1124336| 1123893| 0.09 | 7.2    |
| 40         | BAFSA  | 2246251| 2248279| 2247286| 0.09 | 28.1   |
|            | IBAFSA | 2243074| 2244982| 2244538| 0.08 | 19.4   |
| 60         | BAFSA  | 3366943| 3371770| 3368468| 0.14 | 46.7   |
|            | IBAFSA | 3363378| 3366415| 3364649| 0.09 | 37.1   |
| 100        | BAFSA  | 5609109| 5615624| 5612159| 0.12 | 93.0   |
|            | IBAFSA | 5607516| 5610210| 5608698| 0.05 | 80.1   |

FIGURE 5. UC cost convergence curve for 10 units system.

those of the standard BAFSA. The results show that the proposed IBAFSA provides better solutions than the standard. Meanwhile, it also has an advantage in computing time over the standard. Fig. 5 shows the convergence curve of the total operating cost for a 10-unit UC problem. Compared with the standard, the optimal results and calculation convergence of IBAFSA are significantly improved.

2) COMPARISON OF IBAFSA WITH OTHER METHODS

Table 4 and Table 5 show the optimal results on total operating costs and execution time of IBAFSA and seventeen classical methods for solving 10- to 100-unit UC problems, including LR [30], evolutionary programming (EP) [31], integer-coded genetic algorithm (ICGA) [32], binary fireworks algorithm (BFWA) [33], simulated annealing (SA) [34], IPSO [35], BPSO [10], BDE [12], shuffled frog leaping algorithm (SFLA) [36], harmony search algorithm (HSA) [37], HHSR [11], quantum inspired approximate dynamic programming (QI-ADP) [38], self-adaptive bat algorithm (SABA) [39], MILP [8], quantum-inspired evolutionary algorithm (QEA) [40], imperialistic competition algorithm (ICA) [41], and BGWO [13].

From Table 4, compared with the results of above UC solving methods except for MILP [8], it is known that the proposed one can get the minimum operating costs for 10-unit and 20-unit systems, and get near minimum costs for remaining unit scales, 40- to 100-unit. The proposed method can obtain a near-optimal solution with a lower total operating cost than that of other intelligent optimization algorithms.

From Table 5, it is known that the proposed method takes the minimum execution time for all sizes of test systems among the solving methods listed in the table. It is much speedier than MILP. Its solution time for 100-unit UC is 80.1s while MILP takes 6341s.

According to the results in Table 4 and Table 5, MILP obtains the lowest operation costs for the test systems whose sizes are no more than 100 units, but its solution time increases sharply with the expansion of unit scale. Although a UC problem can be transformed into the MILP model by linearizing the quadratic function, the number of decision variables of the model increases dramatically with system size getting larger.

In recent years, a few researchers have mainly been focused on the UC problems of the 200-unit system and above, and very few can make optimal UC schedules for a 1000-unit system. In this research, the testing results of the proposed method for 200 to 1000-unit systems were obtained and compared with QI-ADP [38] and BDE [12], which are valuable UC methods in recent years, in Table 6. From the table, it is known that the proposed one is faster than the compared ones, and can get a little lower operating costs for several large-scale systems.

Fig. 6 shows the relationship between the execution time and the unit scale. Because the proposers of the QI-ADP method did not present the results for 400- and 600-unit systems in [38], the curve of QI-ADP is not drawn in the figure. In fact, QI-ADP method takes more time to get the optimal UC schedule for a power system (10- to 200-unit, and 1000-unit) than that of IBAFSA. It is seen that IBAFSA has better performance over BDE and QI-ADP in solving large-scale UC problems. The execution time of IBAFSA increases linearly with system size and has a lower rate against time variation compared with BDE and QI-ADP. The proposed fast constraints processing mechanism plays a significant role in speeding up the UC solutions for IBAFSA.

The numerical results show that the proposed method is also effective in solving large-scale UC problems.

3) RESULTS WITH RAMP RATE CONSTRAINT

The actual generation capacity of thermal power units is limited by the ramp rate, which is not considered in the UC calculations of QI-ADP, BDE, and IBAFSA relating to Table 6 and Fig. 6. To make the system more practical, the ramp rate constraints are incorporated in the formulation of the UC problem. It is assumed that the values of $UR_i$ and $DR_i$ are the same and considered as 20% of the units maximum capacity. Table 7 shows the UC solution results for different unit scales taking the ramp rate constraints into account. It can be seen that the total operating costs increase after taking into account the ramp rate constraints.
4) UC WITH EMISSION CONSIDERATION
With the policy of energy-saving and emission reduction being enforced, the objective function of large-scale UC problems should also consider the minimization of environmental costs. The pollutant emission parameters of the 10-unit system are taken from [42] and shown in Table 1. Table 8 shows the optimal operation costs and the corresponding emissions with or without the environmental costs into consideration. According to the table, it is seen that the total operation costs increase a little bit after considering the environmental factor, but the amount of pollutant emissions decreases obviously. The results show that the proposed method is feasible and has the advantages as mentioned in the proceeding paragraphs of this Section, even if the objective function is changed.

### C. TESTS FOR SYSTEMS OF 54 AND 270 UNITS
To further validate the performance of the proposed approach for practical larger power systems, the IEEE 118-bus system consisting of 54 units [43] and the power system with
270 units are tested with all the constraints, including unit ramp rate constraints, involved in the UC problem being considered. The power system with 270 units is extended from the data of the IEEE 118-bus system. Table 9 shows the optimization results for the UC problems of IEEE 118-bus and 270-unit systems. The total operating cost of economic optimum for IEEE 118-bus system is $1643818 in [29], which is slightly higher than that obtained one, $1643805.6, by the proposed UC method. Fig. 7 and Fig. 8 show the UC cost convergence curves of the above systems. The results indicate again that the proposed method has good convergence performance in solving large-scale UC, can be able to find a near-optimal solution even if UC constraints are changed, an example is that it works when unit ramp rates are added into the UC constraints.

**D. CHARACTERISTIC COMPARISON OF PROPOSED METHOD WITH OTHERS**

Based on the simulation results mentioned in Subsection V.B, the solution characteristics of MILP [8], BDE [12], QI-ADP [38], and the proposed method are summarized in Table 10. A UC problem can be transformed into the MILP model by linearizing the quadratic function, and the optimum solution can be obtained when solving the small and medium-sized UC. However, its execution time increases exponentially with system scale growth, and the latest improved MILP can solve a UC problem of a power system with less than 500 generating units [17]. QI-ADP, BDE, and IBAFSA can solve a UC problem of a system with 1000 generating units and obtain a near-optimal solution. Their execution time increases linearly with the system scale. According to Table 6 in Section V, the proposed method can get a little bit lower operating costs than those of QI-ADP and BDE for several large-scale systems with more than 200 units and its execution time is

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**TABLE 7. Optimization results considering ramp constraint.**

| Number of units | Start-up cost/$ | Generation cost/$ | Total cost/$ |
|-----------------|-----------------|------------------|--------------|
| 10              | 4090.0          | 561436.8         | 565526.8     |
| 20              | 8860.0          | 1117842.6        | 1126702.6    |
| 40              | 18940.0         | 2230472.7        | 2249412.7    |
| 60              | 28310.0         | 3342543.9        | 3370853.9    |
| 80              | 37650.0         | 4458345.4        | 4495995.4    |
| 100             | 47640.0         | 5570529.6        | 5618169.6    |

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**TABLE 8. Solution Comparison with/out environmental consideration.**

| Number of units | Economic optimum | Social cost optimum |
|-----------------|------------------|--------------------|
| Emission/lb     | Total cost/$     | Emission/lb        | Total cost/$     |
| 10              | 269906.4         | 563937.7           | 262512.5         | 565561.1        |
| 20              | 546037.5         | 1123297.4          | 535205.7         | 1126704.8       |
| 40              | 1098729.2        | 2243074.3          | 1077785.6        | 2249280.5       |
| 60              | 1649418.6        | 3363377.7          | 1618453.8        | 3369671.5       |
| 80              | 2187802.0        | 4487108.4          | 2160293.2        | 4495597.9       |
| 100             | 2737541.3        | 5607515.9          | 2701084.4        | 5616375.2       |

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**FIGURE 6. Relationship between execution time and unit scale.**

**FIGURE 7. UC cost convergence curve for IEEE 118-bus system.**

**FIGURE 8. UC cost convergence curve for the 270-unit system.**

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**TABLE 9. The result of IEEE 118-bus and 270-unit system.**

| System       | Economic optimum | Social cost optimum |
|--------------|------------------|--------------------|
| Emission/lb  | Total cost/$     | Emission/lb        | Total cost/$     |
| IEEE118      | 238024.5         | 1645805.6          | 231418.2         | 1651201.6       |
| 270-unit     | 1183431.5        | 8251541.0          | 1176280.2        | 8279109.6       |
TABLE 10. Characteristics of MILP, BDE, QI-ADP, and IBAFSA.

| Method | Type of problems to solve | System scale | Property of final solution | Execution time with system scale |
|--------|--------------------------|--------------|---------------------------|----------------------------------|
| MILP   | linear                    | small & medium-scale | optimum                   | exponential growth               |
| QI-ADP | deterministic/stochastic | large-scale   | near-optimal              | linear acceptable                |
| BDE    | discrete                  | large-scale   | optimal                   | linear acceptable                |
| IBAFSA | discrete                  | large-scale   | & better for >200 units   | linear acceptable                |

generally the minimum. Consequently, the proposed method is the best one for a large-scale power system within an acceptable solution time.

VI. CONCLUSION

In this article, the operation economy and pollutant emissions of generating units are comprehensively considered as the objective function of the problem. An improved binary artificial fish swarm algorithm (IBAFSA) and a fast constraint processing mechanism are presented to solve the UC problems of large-scale power systems. It can obtain an optimal solution to the UC of an actual large power system in an acceptable time. The main conclusions of the paper are summarized as follows.

- The convergence performance and global optimization ability of the proposed IBAFSA are better than those of the standard one and has better performance over BDE and QI-ADP in solving large-scale UC problems.
- The proposed fast constraints processing mechanism can handle the coupling problem between system spinning reserve constraint and unit minimum up and down time constraint, which plays a significant role in speeding up the UC solutions.
- The experimental results indicate that the proposed method is of attractive superiority in both solving accuracy and computing time, and is a general method to adapt to the changes of the objective function and constraints of a UC optimization, which has good application prospect.

Future researches include taking the generation uncertainty of new energy resource units into UC models and making the practical application of IBAFSA to a real large-scale power system.

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YONGLI ZHU (Member, IEEE) received the Ph.D. degree from North China Electric Power University, Beijing, China, in 1992. He is currently a Professor with North China Electric Power University. His research interests include power system analysis and control, networked monitoring, and intelligent processing of big power data.

HUI GAO received the bachelor’s degree in electrical engineering from the Xi’an University of Technology, China, in 2018. She is currently pursuing the master’s degree with North China Electric Power University, China. Her research interests include optimal dispatching of power systems and intelligent optimization algorithm.

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