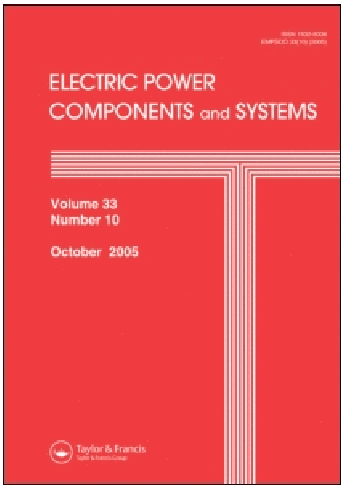

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A Thermal Unit Commitment Approach Using an Improved Quantum Evolutionary Algorithm

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Abstract *This article presents a new approach for solving unit commitment problems using a quantum-inspired evolutionary algorithm. The unit commitment problem is a complicated non-linear and mixed-integer combinatorial optimization problem with heavy constraints. This article proposes an improved quantum evolutionary algorithm to effectively solve unit commitment problems. The quantum-inspired evolutionary algorithm is considered a novel evolutionary algorithm inspired by quantum computing, which is based on the concept and principles of quantum computing such as the quantum bit and the superposition of states. The proposed improved quantum evolutionary algorithm adopts both the simplified rotation gate and the decreasing rotation angle approach in order to improve the convergence performance of the conventional quantum-inspired evolutionary algorithm. The suggested simplified rotation gate can determine the rotation angle without a lookup table, while the conventional rotation gate requires a predefined lookup table to determine the rotation angle. In addition, the proposed decreasing rotation angle approach provides the linearly decreasing magnitude of rotation angle along the iteration. Furthermore, this article includes heuristic-based constraint treatment techniques to deal with the minimum up/down time and spinning reserve constraints in unit commitment problems. Since the excessive spinning reserve can incur high operation costs, the unit decommitment strategy is also introduced to improve the solution quality. To demonstrate the performance of the proposed improved quantum evolutionary algorithm, it is applied to the large-scale power systems of up to 100-unit with 24-hr demand horizon.*

Keywords combinatorial optimization, unit commitment problem, improved quantum evolutionary algorithm, constraint treatment technique

1. Introduction

The unit commitment (UC) problem, one of the most important tasks in short-term operation planning of modern power systems, has a significant influence on secure and economic operation of power systems [1]. The optimal commitment scheduling can not only save millions of dollars for the power companies, but it can also maintain system

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reliability by keeping the proper spinning reserve. The UC problems involve scheduling the on/off states of generating units that minimize the operating cost for a given time horizon. The committed units must meet the system forecasted demand and spinning reserve requirement at minimum operating costs, subject to a large set of operating constraints. The UC problem is mathematically formulated as a non-linear, large-scale, mixed-integer combinatorial optimization problem [2–16]. The number of combinations of 0-1 variables grows exponentially for a large-scale UC problem. Therefore, the UC problem is one of the most difficult in the power system optimization area.

Over the past decades, many salient optimization methods have been developed for solving UC problems. The exact solution to the problem can be obtained only by complete enumeration, which cannot be applied to realistic power systems due to its excessive computation time requirements [1]. Research efforts, therefore, have been concentrated on efficient and near-optimal UC algorithms that can be applied to the realistic power systems and have reasonable storage and computation time requirements. The optimization methods for the UC problem can be divided into two classes through a survey of literature as follows: One includes numerical optimization techniques such as priority list methods [2, 3], dynamic programming [4, 5], Lagrangian relaxation (LR) methods [6, 7], branch-and-bound methods [8], and mixed-integer programming [9]; the other includes stochastic search methods such as genetic algorithms (GAs) [10, 11], evolutionary programming (EP) [12, 13], simulated annealing (SA) [14, 15], and particle swarm optimization (PSO) [16].

Quantum computing is a new paradigm, which has been proposed as a consequence of applying quantum mechanics to computer science [17–23]. Research on quantum computing can be classified into two areas: 1) quantum mechanical computers and 2) quantum algorithms. Quantum mechanical computers have been studied since the early 1980s and are shown to be more powerful than digital computers for solving various specialized problems [18, 19]. Research on merging evolutionary computation and quantum computing has being carried out since the late 1990s and can be classified into two fields. One approach concentrates on studying new quantum algorithms using automatic programming techniques such as genetic programming [20]. The other one focuses on quantum-inspired evolutionary computing for a digital computer as a branch of study on evolutionary computation that is characterized by certain principles of quantum mechanics such as uncertainty, superposition, and interference [17, 21–23]. Quantum-inspired computing was first introduced in [21]. Narayanan and Moore [22] proposed the quantum-inspired GAs, where concepts and principles of quantum mechanics are used to inform and inspire more efficient evolutionary computing methods. Han and Kim [17] proposed a quantum-inspired evolutionary algorithm (QEA), based on the concept and principles of quantum computing such as a quantum bit and superposition of states. The QEA can not only treat the balance between exploration and exploitation more easily but can also explore the search space for a global solution with smaller population size and short computation time in solving the combinatorial optimization problems.

This article proposes an improved quantum evolutionary algorithm (IQEA) for solving UC problems. The proposed IQEA introduces the simplified rotation gate and decreasing rotation angle approach in order to enhance the performance of the conventional QEA. The rotation gate, one of the quantum gates, is used to modify the state of qubit. In the traditional QEA, the rotation gate definitely requires a predefined lookup table to determine the rotation angle [17]. However, the proposed simplified rotation gate can determine the rotation angle without the lookup table. Prior to applying the rotation gate, it is necessary to set the magnitude of rotation angle that has an effect on the speed of convergence and the quality of solution. This article proposes the decreasing rotation angle approach that the magnitude of rotation angle is linearly decreased along the iteration. Furthermore, to effectively satisfy the minimum up/down time and spinning reserve constraints in UC problems, the heuristic-based constraint treatment techniques are proposed in order to improve the solution quality not scarifying the computational efficiency. To prevent high operating costs due to excessive spinning reserve, the unit de-commitment approach is also proposed.

This article is organized as follows. After the introduction, Section 2 describes the mathematical formulations of the UC problem. Section 3 summarizes the QEA, and Section 4 deals with the proposed IQEA for solving UC problems. The proposed constraint-handling techniques are described in Section 5. To verify the effectiveness of the proposed IQEA, test systems of up to 100 units along with 24-hr load demands are tested, and the results are compared with those of previous works in Section 6. Finally, the conclusion is described in Section 7.

2. Forumulation of UC Problem

2.1. *Objective Function*

The objective of the UC problem is to minimize the total operating costs of the generating units during a scheduling horizon, subject to a large set of system and unit constraints [1]. The objective function of the UC problem is expressed as the sum of fuel, start-up, and shut-down costs of all the generating units.

2.1.1. Fuel Cost Function. For all the committed generating units, the total fuel cost is minimized by economically dispatching the units. The fuel cost function of unit j at hour t is expressed as a second order polynomial as follows:

$$F_j(P_{j,t}) = a_j + b_j P_{j,t} + c_j P_{j,t}^2, \tag{1}$$

where $P_{j,t}$ is the power generation of unit j at hour t, and a_j, b_j, and c_j are the cost coefficients of unit j.

2.1.2. Start-up Cost. Start-up cost for restarting a de-committed generating unit, which is related to the temperature of the boiler, should be included in the objective function. That is, the start-up cost depends on the number of hours during which the unit has been off. Start-up cost will be high cold cost ($SU_{C,j}$) when down time duration exceeds cold start hour ($T_{cold,j}$) in excess of minimum down time and will be low hot cost ($SU_{H,j}$) when down time duration does not exceed cold start hour in excess of minimum down times. In general, the start-up cost is described the two-step function as follows:

$$SU_{j,t} = \begin{cases} SU_{H,j} & \text{if } MDT_j \le TOFF_{j,t} \le MDT_j + T_{cold,j} \\ SU_{C,j} & \text{if } TOFF_{j,t} > MDT_j + T_{cold,j} \end{cases}, \tag{2}$$

where $TOFF_{j,t}$ is the duration for which unit j is continuously off-line until hour t, and MDT_j is the minimum down-time of unit j.

2.1.3. Shut-down Cost. Shut-down cost is usually modeled as a constant value for each unit per shutdown. In this article, the shut-down costs have been taken equal to 0 for all units, and it is excluded from the objective function.

Consequently, the objective function of the UC problem is given by the minimization of the following cost function:

$$\min \sum_{t=1}^{T} \sum_{j=1}^{N} [F_j(P_{j,t})u_{j,t} + SU_{j,t}(1 - u_{j,t-1})u_{j,t}], \tag{3}$$

where T is the number of scheduling periods, N is the number of generating units, and $u_{j,t}$ is the on/off status of unit j at hour t. The $u_{j,t}$ is set to be 1 when unit j is on-line, and $u_{j,t}$ is set to be 0 when unit j is off-line.

2.2. System and Unit Constraints

2.2.1. Load Balance Constraints. The sum of unit generation output at each hour must satisfy the system load demand requirement of the corresponding hour as follows:

$$\sum_{j=1}^{N} P_{j,t}u_{j,t} = PD_t, \tag{4}$$

where PD_t is the total system demand at hour t.

2.2.2. Generation Limit Constraints. The power produced by each unit must be within certain limits as indicated below:

$$u_{j,t}P_{j,\min} \le P_{j,t} \le u_{j,t}P_{j,\max}, \tag{5}$$

where $P_{j,\min}$ and $P_{j,\max}$ are the minimum and maximum generation limits of unit j, respectively.

2.2.3. Spinning Reserve Constraints. The spinning reserve must be available during the operation of a power system so as to minimize the probability of load interruption. The spinning reserve is considered to be a pre-specified amount or a given percentage of the forecasted peak demand. Spinning reserve can be specified in terms of excess megawatt capacity, which is expressed by

$$\sum_{j=1}^{N} P_{j,\max}u_{j,t} \ge PD_t + SR_t, \tag{6}$$

where SR_t is the required spinning reserve at hour t.

2.2.4. Generation Ramping Constraints. Due to the mechanical characteristics and thermal stress limitations of a generating unit, the actual operating range of all online units is restricted by their ramp rate limits as follows:

$$RD_j \le P_{j,t} - P_{j,(t-1)} \le RU_j, \tag{7}$$

where RD_j and RU_j are the ramp-down and ramp-up limits of unit j, respectively.

2.2.5. Minimum Up-time/Down-time Constraints. The unit cannot be turned on or off immediately once it is committed or de-committed. The minimum up/down time constraints indicate that a unit must be on/off during a certain number of hours before it becomes shut-down or start-up, respectively. These constraints are given by

$$u_{j,t} = \begin{cases} 1 & \text{if } 1 \leq TON_{j,t-1} < MUT_j \\ 0 & \text{if } 1 \leq TOFF_{j,t-1} < MDT_j \\ 0 \text{ or } 1 & \text{otherwise} \end{cases}, \tag{8}$$

where $TON_{j,t}$ is the duration for which unit j is continuously on-line at hour t and MUT_j is the minimum up-time of unit j.

3. Introduction of Quantum Evolutionary Algorithm

3.1. Quantum Computing Paradigm

The smallest unit of information stored in a two-state quantum computer is called a quantum bit or *qubit* [17]. A qubit is analogous to a bit of storage in a traditional computer. A qubit may be in the "1" state, in the "0" state, or in any superposition of the two, while a bit in the traditional computing can only hold a single state, either 0 or 1. To illustrate this, traditional 0 and 1 values are commonly written as $|0\rangle$ and $|1\rangle$, and the state of a qubit can be represented as follows:

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle, \tag{9}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ denote the probability that the qubit will be found in 0 state and 1 state. Normalization of the state to unity guarantees $|\alpha|^2 + |\beta|^2 = 1$. The state of a qubit can be changed by the operation with a quantum gate such as NOT gate, rotation gate, and Hadamard gate, etc.

3.2. QEA

QEA, developed by Han and Kim [17], is designed with a novel Q-bit representation. A *Q-bit* is defined as the smallest unit of information in a QEA, which is defined with a pair of numbers (α, β) as $[{\alpha \atop \beta}]$, where $|\alpha|^2 + |\beta|^2 = 1$. A *Q-bit individual* as a string of n Q-bits is defined as

$$q = \left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_n \\ \beta_1 & \beta_2 & \cdots & \beta_n \end{array}\right], \tag{10}$$

where $|\alpha_j|^2 + |\beta_j|^2 = 1$ $(j = 1, 2, \ldots, n)$. The Q-bit representation has the advantage that it is able to represent a linear superposition of states. All possible combinations of values of the decision variables can be derived from a single representation, while a system of n bits has 2^n possible single states in the classical computing.

Evolutionary computing with Q-bit representation has a better characteristic of population diversity than other representations since it can probabilistically represent the linear superposition of states. For searching in parallel like other evolutionary algorithms (EAs), a population of Q-bit individuals at the kth iteration is represented as follows:

$$Q(k) = \{q_1^k, q_2^k, \ldots, q_{NP}^k\}, \tag{11}$$

where NP is the population size, and q_i^k $(i = 1, 2, \ldots, NP)$ is a Q-bit individual defined as follows:

$$q_i^k = \left[\begin{array}{c|c|c|c} \alpha_{i1}^k & \alpha_{i2}^k & \cdots & \alpha_{in}^k \\ \beta_{i1}^k & \beta_{i2}^k & \cdots & \beta_{in}^k \end{array}\right]. \tag{12}$$

The binary solutions $X(k) = \{X_1^k, X_2^k, \ldots, X_{NP}^k\}$ can be obtained by observing the state of $Q(k)$. Here, a binary solution $X_i^k = \{x_{i1}^k, x_{i2}^k, \ldots, x_{in}^k\}$ $(i = 1, 2, \ldots, NP)$ is a binary string, which is formed by selecting either 0 or 1 for each bit using the probability, either $|\alpha_i^k|^2$ or $|\beta_i^k|^2$, respectively. After evaluating the fitness value of each binary solution, the best solution of each individual is stored in the best solution string $B_i^k = \{b_{i1}^k, b_{i2}^k, \ldots, b_{in}^k\}$ $(i = 1, 2, \ldots, NP)$, and then the best solution among $B(k) = \{B_1^k, B_2^k, \ldots, B_{NP}^k\}$ is stored in the global solution string $G(k) = \{g_1^k, g_2^k, \ldots, g_n^k\}$.

A rotation gate $U(\Delta\theta_{ij})$, $U(-\Delta\theta_{ij})$ when q_{ij} is located on the second or fourth quadrant, is employed as a variation operator of QEA, by which all Q-bit individuals are updated. $(\alpha_{ij}, \beta_{ij})$ of the jth Q-bit in the ith Q-bit individual at iteration $k+1$ is updated. The following and the updated Q-bit should satisfy the normalization condition $|\alpha_{ij}^{k+1}|^2 + |\beta_{ij}^{k+1}|^2 = 1$:

$$\begin{bmatrix} \alpha_{ij}^{k+1} \\ \beta_{ij}^{k+1} \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_{ij}^{k+1}) & -\sin(\Delta\theta_{ij}^{k+1}) \\ \sin(\Delta\theta_{ij}^{k+1}) & \cos(\Delta\theta_{ij}^{k+1}) \end{bmatrix} \begin{bmatrix} \alpha_{ij}^k \\ \beta_{ij}^k \end{bmatrix}, \tag{13}$$

where, $\Delta\theta_{ij}$ is a rotation angle of the jth Q-bit toward either 0 or 1 state. Here, the value of $\Delta\theta_{ij}$ is determined through a predefined lookup table [17] as described in Table 1.

Table 1
Example of lookup table for determining rotation angle

x_{ij}	b_{ij}	$Fitness(X_i) \geq Fitness(B_i)$	$\Delta\theta_{ij}$
0	0	False	θ_1
0	0	True	θ_2
0	1	False	θ_3
0	1	True	θ_4
1	0	False	θ_5
1	0	True	θ_6
1	1	False	θ_7
1	1	True	θ_8

The general procedure of a QEA is summarized as the following pseudocode.

```
Begin
  k ← 0
  Initialize the Q-bit individuals (i.e., Q(k)).
  Make the binary solutions in X(k).
  Store the best solutions among X(k) into B(k).
    While (k < maximum iteration)
      k ← k + 1
      Update Q(k) using rotation gate.
      Make X(k) by observing the state of Q(k).
      Store the best solutions among B(k − 1) and X(k) into B(k).
      Store the best solution among B(k) into G(k).
    End
End
```

4. IQEA for UC Problem

4.1. Simplified Rotation Gate and Decreasing Rotation Angle Approach

4.1.1. Simplified Rotation Gate. The proposed IQEA introduces two effective techniques compared to the conventional QEA: 1) a simplified rotation gate for updating Q-bits and 2) a decreasing rotation angle approach for determining the magnitude of the rotation angle. In the conventional QEA, the rotation gate requires a pre-specified lookup table to determine the rotation angle $\Delta\theta$ to obtain the new (α, β). The proposed simplified rotation gate determines the rotation angle without the lookup table information as described in Eq. (14):

$$\Delta\theta_{ij,t}^{k+1} = \theta \times \gamma_i^k \times (b_{ij,t}^k - x_{ij,t}^k), \tag{14}$$

where t is the index of time ($t = 1, 2, \ldots, T$), and γ_i^k can be obtained by comparing the fitness of the current binary solution with that of best solution as follows:

$$\gamma_i^k = \begin{cases} 0 & \text{if } f(X_i^k) \le f(B_i^k) \\ 1 & \text{otherwise} \end{cases}, \tag{15}$$

where $f(\cdot)$ is the value of the object function.

4.1.2. Decreasing Rotation Angle Approach. The magnitude of rotation angle (*i.e.*, θ) has an effect to the quality of solution and the speed of convergence. Therefore, the proper selection of θ may not only lead to a balance between global exploration and local exploitation but also result in less iteration on average to find the optimal solution. In general, the values from 0.001π to 0.05π are recommended for the magnitude of rotation angle, although they depend on the problems [17]. This article proposes an efficient rotation angle approach for determining the magnitude of the rotation angle in order to enhance the convergence characteristics. In the proposed approach, the magnitude of rotation angle decreases monotonously from $\theta_{\max}$ to $\theta_{\min}$ along the iteration as follows:

$$\theta = \theta_{\max} - (\theta_{\max} - \theta_{\min}) \times \frac{k}{iter_{\max}}. \tag{16}$$

Here, $iter_{\max}$ corresponds to the maximum iteration number, and k is the current iteration number.

4.2. Implementation of IQEA for UC Problems

Since UC problems in power systems involve determining the on/off states of generating units that minimize the operating cost for a given time horizon, the decision variables correspond to on/off status of generating units. Figure 1 illustrates the structure of a population of the proposed IQEA for UC problems. The $x_{ij,t}$ is set to be 1 if the jth generator in the ith individual at hour t is ON; otherwise $x_{ij,t}$ is set to be 0. After determining the optimal combination of commitment scheduling, the optimal power outputs of the committed units are determined through the conventional economic dispatch (ED) procedure. Since the fuel cost function of a generating unit is approximately represented as a quadratic function described in Eq. (1), the ED problem can be solved by the numerical techniques. In the subsequent sections, the detailed procedures of the IQEA for scheduling the on/off states of units are described.

4.2.1. Creating Initial Q-bit Individual and Binary Solution. In the initialization process, $\alpha^0_{ij,t}$ and $\beta^0_{ij,t}$ of all Q-bit individuals are set to be $1/\sqrt{2}$. It means that a Q-bit individual represents the linear superposition of all possible states with the same probability. The initial binary solutions of a set of individuals are determined by probability stored in the initialized Q-bit individuals. After generating a random number $rn_{ij,t}$, an initial value of the jth element in the ith individual at hour t (*i.e.*, $x^0_{ij,t}$) takes a value of 1 if $rn_{ij,t}$ is less than 1/2; otherwise $x^0_{ij,t}$ is set to be 0. The initial best solutions of individuals (*i.e.*, $B(0)$) are set as their initial binary solutions, and the initial global solution string (*i.e.*, $G(0)$) is determined as the binary solution of the individual with the minimum cost.

4.2.2. Q-bit Individual Update. Q-bit individuals are updated by using the proposed simplified rotation gate, Eqs. (13) to (16). After setting the magnitude of rotation angle

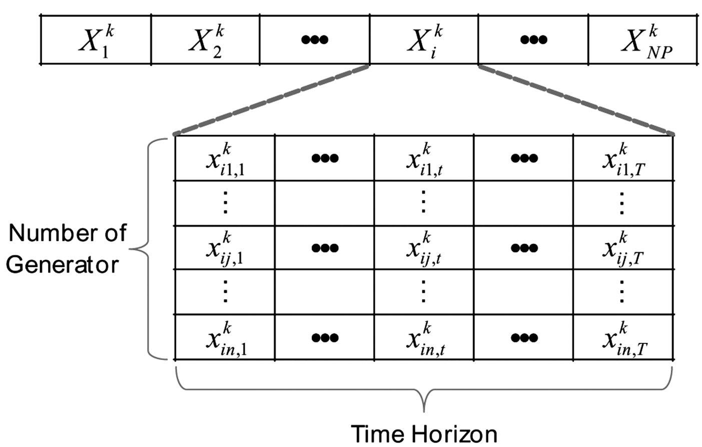

Figure 1. Structure of a population of IQEA for UC problems.

using Eq. (16), the proposed simplified rotation gate determines the rotation angle $\Delta\theta$ for each Q-bit using Eqs. (14) and (15). Then a new pair of (α, β) of each Q-bit in Q-bit individuals is obtained by using Eq. (13).

4.2.3. Modification of Binary Solution. The binary solution of the ith individual at iteration k (*i.e.*, $X_i^k = \{x_{i1}^k, x_{i2}^k, \ldots, x_{in}^k\}$) is modified by probability stored in the ith Q-bit individual as follows:

$$x_{ij,t}^k = \begin{cases} 1 & \text{if } rn_{ij,t} < |\beta_{ij,t}^k|^2 \\ 0 & \text{otherwise} \end{cases}, \tag{17}$$

where $rn_{ij,t}$ is a random number between 0 and 1.

4.2.4. Update of $B(k)$ and $G(k)$. The best solution string of each individual at iteration $k+1$ is updated. If the modified binary solution (*i.e.*, X_i^{k+1}) yields a smaller cost function value than B_i^k, then B_i^{k+1} is set to X_i^{k+1}. Otherwise, the B_i^k is retained:

$$B_i^{k+1} = \begin{cases} X_i^{k+1} & \text{if } f(X_i^{k+1}) \le f(B_i^k) \\ B_i^k & \text{otherwise} \end{cases}. \tag{18}$$

Then, $G(k+1)$ is set as the best evaluated solution among $B(k+1)$.

4.2.5. Stopping Criteria. The proposed IQEA method is terminated if the iteration reaches a pre-specified maximum iteration.

5. Constraint-handling Techniques

Michalewicz and Schoenauer [24] surveyed and compared several constraint-handling techniques used in EAs. Penalty functions are the most popular methods in EAs to handle the system constraints due to their simple concept and convenience for implementation. However, these methods have certain weaknesses in that the penalty functions tend to be ill-behaved near the boundary of the feasible region when the penalty parameters are sufficiently large [25]. To overcome the drawbacks of penalty functions, therefore, this article proposes the efficient heuristic-based constraint treatment methods.

It is very important to create a population satisfying the constraints in solving UC problems. This article proposes the constraint-handling techniques for the minimum up/down time and the spinning reserve constraints. In the evolutionary process for solving UC problems, random bit flipping of state variables occurs; thereby, the constraints may be frequently violated. In this article, therefore, heuristic-based repair algorithms are proposed to accelerate the solution quality and to avoid generating infeasible solutions. To reduce the operating costs incurred by the excessive spinning reserve, the unit de-commitment approach is also proposed.

5.1. Minimum Up-time and Down-time Constraints

While modifying the binary solution of each individual, the minimum up/down time constraints should be satisfied. To do this, this article proposes a heuristic-based constraint treatment technique, as illustrated in the following pseudocode:

```
Begin
  For j = 1 to MaxUnit
    If unit j is set to be on at hour t (i.e., u_{j,t} = 1) then
      If u_{j,t-1} = 0 then
        If TOFF_{j,t-1} < MDT_j then u_{j,t} = 0
        Elseif TOFF_{j,t-1} ≥ MDT_j then u_{j,t} = 1
        Endif
      Elseif u_{j,t-1} = 1 then u_{j,t} = 1
      Endif
    Elseif u_{j,t} = 0 then
      If u_{j,t-1} = 1 then
        If TON_{j,t-1} < MUT_j then u_{j,t} = 1
        Elseif TON_{j,t-1} ≥ MUT_j then u_{j,t} = 0
        Endif
      Elseif u_{j,t-1} = 0 then u_{j,t} = 0
      Endif
    Endif
  Next j
End
```

5.2. *Spinning Reserve Constraints*

Adequate spinning reserves are required to maintain the system reliability for a given time horizon. If the spinning reserve constraint is violated, the system suffers from deficiency of units. This article proposes an efficient heuristic-based repair method, which is launched when the spinning reserve is deficient at any scheduling period, in order to avoid infeasible solutions. In the proposed repair process, de-committed units are forced to turn on until the spinning reserve constraint is satisfied, as shown in Figure 2.

5.3. *Unit De-commitment for Excessive Spinning Reserve*

Excessive spinning reserve is not desirable due to the high operation costs. Therefore, this article proposes a heuristic-based unit de-commitment process to reduce the excessive spinning reserve, leading to cost savings, as illustrated in Figure 3. The unit de-commitment process is performed after obtaining the solutions satisfying the minimum up/down time and the spinning reserve constraints.

6. Numerical Tests

The proposed IQEA is initially tested on the system of ten generating units along with a 24-hr time horizon. The unit characteristics of the base 10-unit system and the demand are given in [10]. Subsequently, the 20-, 40-, 60-, 80-, and 100-unit data are obtained by duplicating the base case (i.e., 10-unit system), and the load demands are adjusted in proportion to the system size. In all cases, the spinning reserve requirements are assumed to be 10% of the hourly demand. For each test case, 30 independent trials are executed to

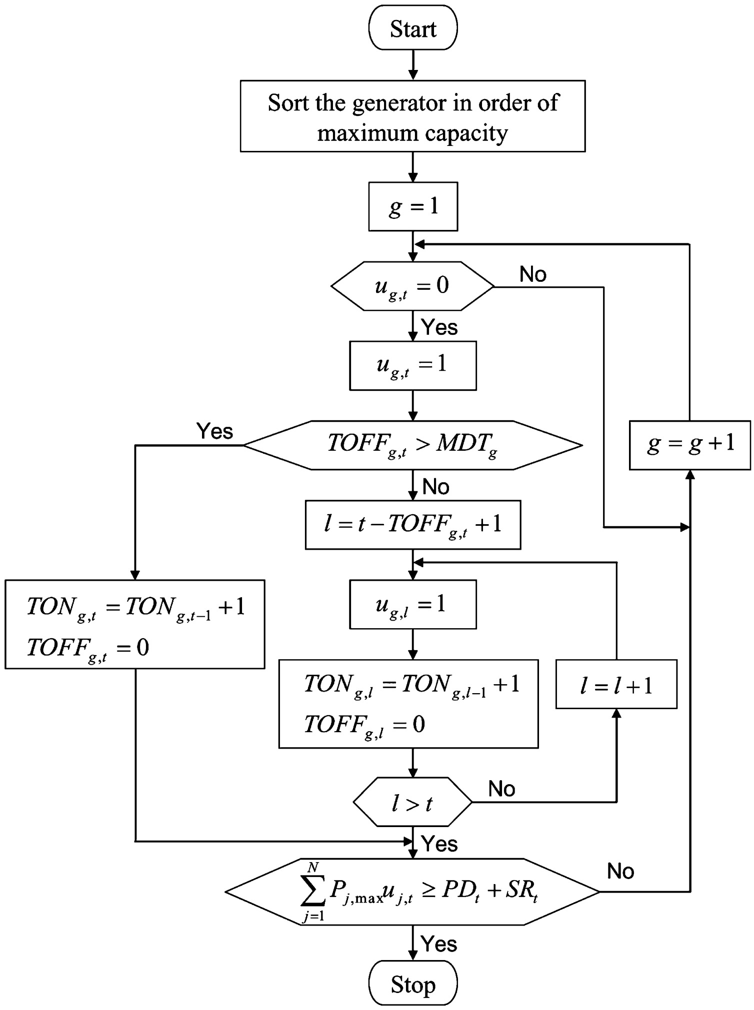

Figure 2. Flowchart of repair algorithm for handling spinning reserve constraint.

compare the solution quality and convergence characteristics. To verify the performance of the proposed IQEA in solving UC problems, simulation results are compared with those of the state-of-the-art methods. Numerical tests have been executed on a Pentium IV 2.0GHz computer.

For implementing the proposed IQEA method, some parameters must be determined in advance. As for the linearly decreasing rotation angle, the starting value (*i.e.*, $\theta_{\max}$) and the ending value (*i.e.*, $\theta_{\min}$) are set as 0.05π and 0.01π, respectively [17]. The maximum iteration $iter_{\max}$ is set as 1000. The population size *NP* is determined throughout the experiments for the 100-unit system with different population sizes. As shown in Figure 4, the solution quality is continuously and marginally improved when increasing the population size while the computation time is linearly increased. Throughout the heuristic trade-off analysis between the solution quality and the computation time, the value for *NP* is selected as 30.

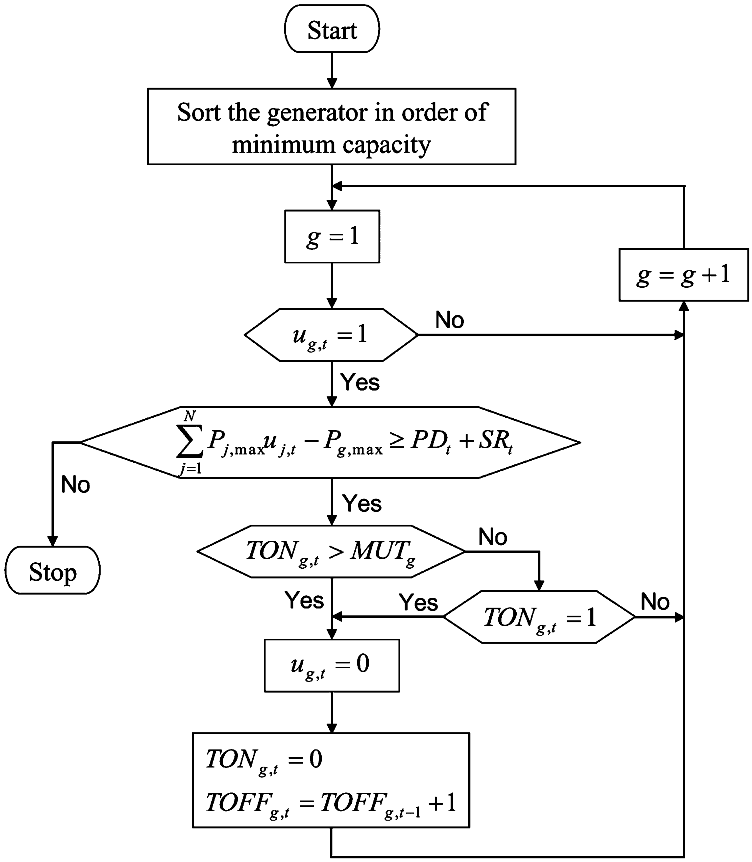

Figure 3. Flowchart of unit de-commitment for prevention of excessive spinning reserve.

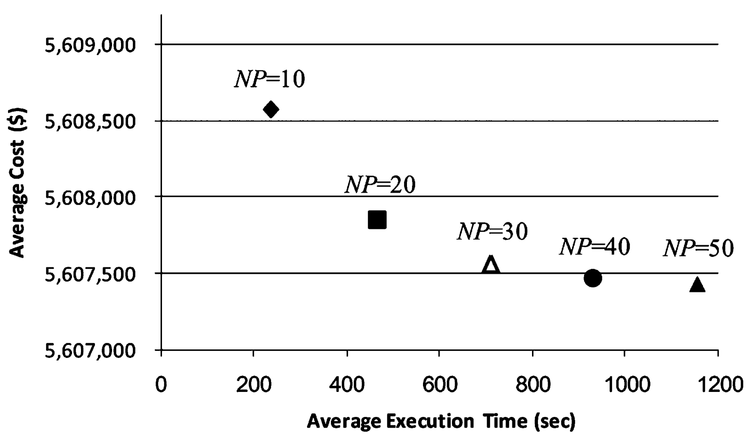

Figure 4. Average cost and computation time for 100-unit system by population sizes.

Table 2
Simulation results of the proposed IQEA method

Units	Best cost ($)	Average cost ($)	Worst cost ($)	Standard deviation
10	563,977	563,977	563,977	0.00
20	1,123,890	1,124,320	1,124,504	126.28
40	2,245,151	2,246,026	2,246,701	377.90
60	3,365,003	3,365,667	3,366,223	309.36
80	4,486,963	4,487,985	4,489,286	501.35
100	5,606,022	5,607,561	5,608,525	577.74

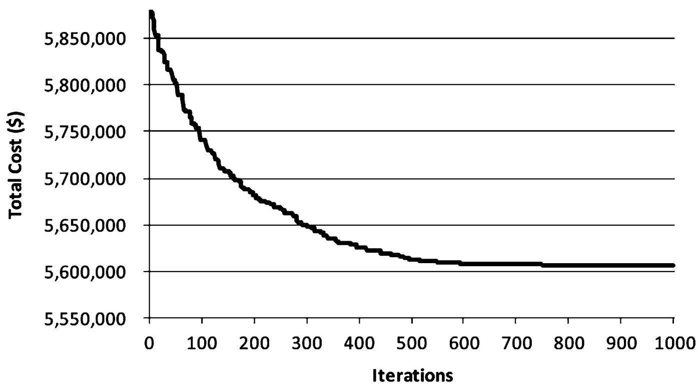

Figure 5. Convergence characteristics of best solution for 100-unit system by IQEA.

Table 3
Comparison of best results of each method for the test systems

Units	LR [10]	GA [10]	EP [12]	SA [15]	IPSO [16]	IQEA
10	565,825	565,825	564,551	565,828	**563,954**	563,977
20	1,130,660	1,126,243	1,125,494	1,126,251	1,125,279	**1,123,890**
40	2,258,503	2,251,911	2,249,093	2,250,063	2,248,163	**2,245,151**
60	3,394,066	3,376,625	3,371,611	N/A	3,370,979	**3,365,003**
80	4,526,022	4,504,933	4,498,479	4,498,076	4,495,032	**4,486,963**
100	5,657,277	5,627,437	5,623,885	5,617,876	5,619,284	**5,606,022**

In Table 2, the best, average, worst cost, and standard deviation achieved by the proposed IQEA are summarized. Figure 5 illustrates the convergence characteristics of best solution for 100-unit system by IQEA.

In Table 3, the best results of the proposed IQEA are compared with those of (LR) [10], GA [10], EP [12], SA [15], and improved particle swarm optimization (IPSO) [16]. Table 3 shows that the proposed method is obviously superior to the existing methods, although the IQEA could not obtain a better solution than IPSO for the 10-unit system. For the 10-unit and 100-unit systems, the commitment schedules during

Table 4
Unit scheduling result and generation cost for 10-unit system

Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	Total power (MW)	Fuel cost ($)	Startup cost ($)
	Generation output (MW)												
1	455	245	0	0	0	0	0	0	0	0	700	13,683	0
2	455	295	0	0	0	0	0	0	0	0	750	14,554	0
3	455	370	0	0	25	0	0	0	0	0	850	16,809	900
4	455	455	0	0	40	0	0	0	0	0	950	18,598	0
5	455	390	0	130	25	0	0	0	0	0	1000	20,020	560
6	455	360	130	130	25	0	0	0	0	0	1100	22,387	1100
7	455	410	130	130	25	0	0	0	0	0	1150	23,262	0
8	455	455	130	130	30	0	0	0	0	0	1200	24,150	0
9	455	455	130	130	85	20	25	0	0	0	1300	27,251	860
10	455	455	130	130	162	33	25	10	0	0	1400	30,058	60
11	455	455	130	130	162	73	25	10	10	0	1450	31,916	60
12	455	455	130	130	162	80	25	43	10	10	1500	33,890	60
13	455	455	130	130	162	33	25	10	0	0	1400	30,058	0
14	455	455	130	130	85	20	25	0	0	0	1300	27,251	0
15	455	455	130	130	30	0	0	0	0	0	1200	24,150	0
16	455	310	130	130	25	0	0	0	0	0	1050	21,514	0
17	455	260	130	130	25	0	0	0	0	0	1000	20,642	0
18	455	360	130	130	25	0	0	0	0	0	1100	22,387	0
19	455	455	130	130	30	0	0	0	0	0	1200	24,150	0
20	455	455	130	130	162	33	25	10	0	0	1400	30,058	490
21	455	455	130	130	85	20	25	0	0	0	1300	27,251	0
22	455	455	0	0	145	20	25	0	0	0	1100	22,736	0
23	455	420	0	0	25	0	0	0	0	0	900	17,685	0
24	455	345	0	0	0	0	0	0	0	0	800	15,427	0

a planning horizon obtained by the proposed IQEA are described in Tables 4 and 5, respectively.

Figure 6 illustrates the scaling of the execution time of the proposed IQEA with the system size. As shown in Figure 6, the execution time increases in a quadratic way with the number of units, and the approximate time of more than 100-unit systems may be predicted from this curve. This implies that the suggested IQEA can be a candidate optimizer for the practical large-scale UC problems.

7. Conclusions

This article suggests a new UC solution technique based on a QEA. The QEA is based on the concept and principles of quantum computing, such as the quantum bit and the superposition of states, and is developed for solving the combinatorial optimization problems with smaller population size and short computation time. For solving UC problems, this article proposes an IQEA. The suggested IQEA introduces the simplified rotation gate and the decreasing rotation angle approach in order to enhance the performance of the conventional QEA. In the proposed IQEA, the simplified rotation gate determines the rotation angle without the predefined lookup table information, and the decreasing rotation

Table 5
Commitment scheduling result for 100-unit system

Hour	Unit schedule
1	1111111111111111111100000000000000000000000000000000000000000000000000000000000000000000000000000000
2	1111111111111111111100000000000000000000000000000000000000000000000000000000000000000000000000000000
3	1111111111111111111100000000000000000000000000010100000000000000000000000000000000000000000000000000
4	1111111111111111111100000000000000000001000000110111011100000000000000000000000000000000000000000000
5	1111111111111111111100100000000011000100111111011100000000000000000000000000000000000000000000000000
6	1111111111111111111100101101011011001110111111111100000000000000000000000000000000000000000000000000
7	1111111111111111111101101111111011011110111111111100000000000000000000000000000000000000000000000000
8	1111111111111111111111111111111111111111111111111100000000000000000000000000000000000000000000000000
9	1111111111111111111111111111111111111111111111111100101111111010101010000000000000000000000000000000
10	1111111111111111111111111111111111111111111111111111111111111111111111110001001110000000010001000000
11	1111111111111111111111111111111111111111111111111111111111111111111111111111111111100000110001001001
12	1111111111111111111111111111111111111111111111111111111111111111111111111111111111110011111111111111
13	1111111111111111111111111111111111111111111111111111111111111111111111001000011000100001000100010010
14	1111111111111111111111111111111111111111111111111101011111011101010010000000000000000000000000000000
15	1111111111111111111101111111110110100111111111111100011111010000010000000000000000000000000000000000
16	1111111111111111111101111111110110100111111111111100000000000000000000000000000000000000000000000000
17	1111111111111111111101111111110110100111111111111100000000000000000000000000000000000000000000000000
18	1111111111111111111101111111110110100111111111111100000000000000000000000000000000000000000000000000
19	1111111111111111111101111111110110100111111111111110100000100011110101000000000000000000000000000000
20	1111111111111111111111111111111111111111111111111111111111111111111111110000101000001111100000000000
21	1111111111111111111111111101111111111011111101011111111111111111111111100000000000000000000000000000
22	1111111111111111111110111000001011011001111000010101011111011100001010000000000000000000000000000000
23	1111111111111111111110000000001001011000010000000000000000000000000000000000000000000000000000000000
24	1111011111111101111110000000001001011000000000000000000000000000000000000000000000000000000000000000

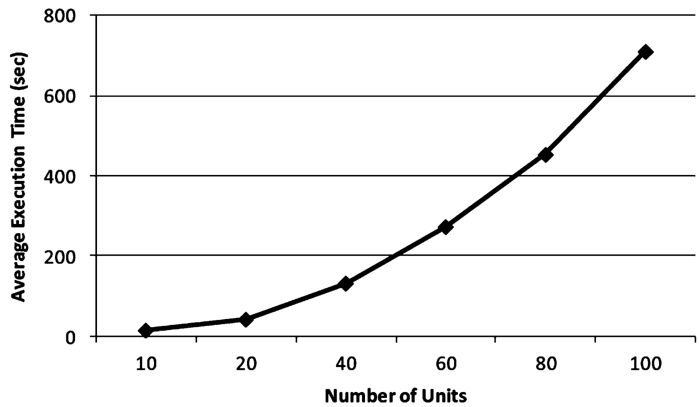

Figure 6. Scaling of the average execution time of the proposed IQEA.

angle approach provides the magnitude of rotation angle linearly decreasing along the iteration. In addition, this article proposes heuristic-based constraint treatment techniques for handling the minimum up/down time and spinning reserve constraints in UC problems. The unit de-commitment approach is also proposed in order to prevent the excessive spinning reserve for cost savings. To verify the performance of the proposed method, the IQEA was applied to test power systems of up to 100 units along with 24-hr load demands; the results are compared with those of previous works. The simulation results obviously show that the proposed IQEA can be used as an excellent optimizer in solving the UC problems.

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