Unit commitment problem solution using Local Attracting Quantum PSO algorithm

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Abstract. In power systems, the demand is time-varying throughout the day, week and month. For that reason, the generators have to be scheduled optimally to increase the saving in the power system by applying the Unit Commitment (UC) to the power system. UC is the operation of turning the generators ON and OFF to supply the demand power. This paper suggests Local Attracting Quantum Particle Swarm Algorithm (LAQPSO) to solve the unit commitment dilemma in power systems. The local attractor in the LAQPSO algorithm is utilized to obtain the rotation angle direction and magnitude in order to update the quantum angle by the quantum rotation gate. The proposed algorithm is applied to solve the UC problem for a 10-units power system. A comparison with different techniques in the literature was implemented to validate the efficiency and the accuracy of the proposed algorithm. The results show the superior performance of the proposed LAQPSO algorithm to minimize the total cost when compared to the literature works.

1. Introduction

Most power systems supply their services to the customers in a cycle pattern due to the activities of the human being. The demand that has to be supplied from the power system is higher at the day time and the first hours of the evening and become less in the morning and the late hours of the evening [1]. Nowadays, various power generation resources such as hydro, steam, nuclear, gas and diesel power plants are found in the power system. Therefore, the decision must be made to operate these power stations economically and make some of them synchronized with the power system and the others in the off state according to the cost of power they produce so as to minimize the total operation cost in the power system [2]. The procedure of making some of the generators in the state ON and other generators in the state OFF can be defined as unit commitment. There are some constraints that must be satisfied in the solution of the unit commitment problem while supplying the demand power. The first types of these constraints are related to the power system such as the transmission constraints and the power reserve constrains that will be needed in the case of demand increase or generator outage from the power system while the second types of constraints has a direct relation with the generators such ramp-down limit, ramp-up limit, minimum up and downtimes[3]. In the large power systems, a high number of generators found to meet the power demand, therefore unit commitment must be employed to get the minimum operation cost and this can be made with the aid of special software that will give the near-optimum schedule for the generation units.

As a result, research endeavors focused on finding algorithms to have an efficient, optimum or near optimum solution to the UC problem[4]. Many classical methods have been used to solve the UC problem such as Dynamic Programming (DP) [5], Branch and Bound (BB) [6], [7], Lagrange
Relaxation (LR) [8], Priority List (PL) [9], Mixed Integer Programming (MIP) [10] and Interior Point Method (IPM) [11]. The performance of these methods is acceptable because they are exact and simple only for power systems with moderate size.

Recently, meta-heuristic algorithms have been used instead of the classical methods because the power system became larger and more complex. The examples of the meta-heuristic methods are the Genetic Algorithm (GA) [12], Particle Swarm Optimization (PSO) [13]–[16], Simulated Annealing (SA) [17] and Ant Colony Search Algorithm (ACSA) [18].

Researchers began to enhance the optimization methods by merging two methods together because these individual optimization algorithms may find the solution in the local minimum. Examples for these merged algorithms are Quantum Inspired Binary PSO Algorithm (QBPSO) [19], [20], Improved Lagrangian Relaxation with Cuckoo Search Algorithm (LR-CSA) [21], Neural-Based Tabu Search (NBTS) [4], hybrid PSO, Grey Wolf Optimizer (PSO-GWO) [2], and Quasi-Oppositional Teaching Learning Based Algorithm (QOTLBO) [22].

This paper applied an improved algorithm which is the product of the hybridization of the PSO algorithm and Quantum computing with Local Attracting (LAQPSO) discovered by Shao and Fei in 2016 [23]. The hybrid style LAPSO has been applied to overcome the drawbacks of PSO algorithm such as lower convergence speed and trapping in the local minimum solution for the solving of the unit commitment problem.

2. MATHEMATICAL FORMULATION FOR UNIT COMMITMENT PROBLEM

The aim of formulating the UC problem is to minimize the overall operation cost during a given time horizon with all of the constraints being satisfied [1]. Therefore, the cost function must be developed and it is the sum of the fuel cost, the start-up cost and the shutdown cost of all the generators according to the state of the generator ON or OFF. The total operation cost can be expressed as in the following equation:

$$C_{total} = \sum_{k=1}^{T} \sum_{g=1}^{N} [f_{gk}(P_{gk}) + STC_{gk}(1-U_{gk})]U_{gk}$$

where \( T \) is the time horizon, \( k \) is the index of time, \( N \) is the number of generators, \( g \) is the index of the generator, \( f_{gk} \) is the fuel cost function, \( U_{gk} \) is the generator (\( g \)) state which takes a state of \( 0 \) or \( 1 \) at hour \( k \), \( P_{gk} \) is the delivered power from the generator (\( g \)) at the hour \( k \), \( STC_{gk} \) is the cost needed to start-up the generator (\( g \)) at the hour \( k \) and \( SDC_{gk} \) is the shutdown cost of the generator (\( g \)) at the hour \( k \).

The fuel cost function is a quadratic function and can be represented by the following equation:

$$f_{gk}(P_{gk}) = c_{g}(P_{gk})^2 + b_{g}(P_{gk}) + a_{g}$$

where \( a_{g}, b_{g} \) and \( c_{g} \) are the fuel cost coefficients.

The thermal unit pressure and temperature must be raised to a certain level so the unit can be online after it has been uncommitted. This raise in temperature and pressure can be made by burning fuel in the boiler and the burned fuel energy results in a zero MW generation from the thermal unit [1]. This expended energy is known as the start-up cost and it depends on the temperature of the boiler or it depends on the time that the generator is uncommitted from the power system.

The start-up cost can be characterized by the following equation:

$$STC_{gk} = \begin{cases} 
HSC_{g} & \text{if } MDT_{g} \leq T_{g}^{off} \leq MDT_{g} + CSH_{g} \\
CS_{g} & \text{if } T_{g}^{off} > MDT_{g} + CSH_{g}
\end{cases}$$

where \( HSC_{g}, \ CS_{g} \) are the hot and cold start-up costs of the generator (\( g \)); \( CSH_{g} \) is the cold start hours of the generator (\( g \)); \( MUT_{g} \) is the minimum up time that the generator (\( g \)) must be in the ON
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state, \( \text{MDT}_g \) is the minimum downtime of the generator \( (g) \) which is the time that the generator \( (g) \) must satisfy before starting it. \( (T_{g^{on}}) \) is the time of the unit \( g \) is continuously OFF.

The objective function of the unit commitment must satisfy a set of constraints and these constraints can be divided into two categories:

(A) System constraints also are known as coupling constraints [24]. All the generators that in the ON state and connected to the power system are governed by the coupling constraints ignoring the efficiency or the age of the generators and taking into consideration the following:

1. The summation of the power supplied by the generators is equivalent to the demand power \( D_k \) at every hour.

\[
\sum_{g=1}^{N} P_{gk} U_{gk} = D_k
\]  

(4)

2. Spinning reserve constraint is applied to deal with the extra change in the demand power and in the situation of the generator outage or a transmission line out of service, therefore the power reserve is used to compensate for the lack in the power supplied.

\[
\sum_{g=1}^{N} P_{g}^{\max} U_{gk} \geq D_k + R_k
\]  

(5)

where \( D_k \) is the load demand of the system at the hour \( k \) and \( R_k \) is the spinning reserve of the power system at the same hour.

(B) Generator constraints also are known as local constraints because they are related to the generator and divided into:

1. The generator has upper and lower limits while generating power and these limits cannot be exceeded.

\[
P_{g}^{\max} \geq P_{gk} \geq P_{g}^{\min}
\]  

(6)

where \( P_{g}^{\max}, P_{g}^{\min} \) are the maximum and minimum power that can be supplied from the unit \( g \).

2. The minimum time of continuous operation is known as the minimum uptime (MUT).

\[
T_{g}^{on} \geq \text{MUT}_g
\]  

(7)

where \( T_{g}^{on} \) is the continuous ON time of the generator \( (g) \)

3. The generator must be in the OFF state for a time that equals the minimum downtime (MDT).

\[
T_{g}^{off} \geq \text{MDT}_g
\]  

(8)

3. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle Swarm Optimization (PSO) was presented by James Kennedy and Russell Eberhart in 1995 [25]. It was introduced as an alternative to the genetic algorithm. As a comparison with evolutionary algorithms, the PSO algorithm is easy to program and implement with less setting of the parameters [23]. As a result, it has the privilege as a contender in the numerical optimization fields. The PSO consist of a flock of individuals moves in the search space to find the solution for the problem. These individuals share their experiences with each other; therefore, PSO algorithm is a population-based optimization searching algorithm. The movement of each particle in the space area for searching the optimality according to the particle current velocity, the particle past experience, and the neighbouring particles experience [19]. Every individual has a position vector and a velocity vector denoted as X and V respectively. In a defined search space, the position and the velocity of each particle in the PSO algorithm is updated by using the vector of the best personal experience \( P_{best} \) in which the best previous position of the particle is recorded and the group or global best experience \( G_{best} \) vector which is also a records the best position of individuals in the swarm.

The velocity and the position of the particles can be updated using the following equations:
\[ V_r^{m+1} = \omega V_r^m + c_1 \varphi_1(P_{best_r}^m - X_r^m) + c_2 \varphi_2(G_{best}^m - X_r^m) \]  
\[ X_r^{m+1} = X_r^m + V_r^{m+1} \]

where \( (X_r^m, V_r^{m+1}) \) are the \( r \)th particle position and speed at the current iteration \( m \), \((c_1, c_2)\) are acceleration factors known as cognitive and social factors respectively, \((\varphi_1, \varphi_2)\) are two random numbers uniformly between 0 and 1, \( \omega \) is the inertia factor that controls the movement of the particles and \( \omega \) can be taken as a constant number or represented as in the following equation:

\[ \omega = \omega_{\text{max}} - \frac{(\omega_{\text{max}} - \omega_{\text{min}})}{\text{iter}_{\text{max}}} \times m \]

where \( \text{iter}_{\text{max}} \) is the maximum number of iterations, \((\omega_{\text{max}}, \omega_{\text{min}})\) are the maximum and minimum values of the inertia factor. Typically, \((\omega_{\text{max}}, \omega_{\text{min}})\) are taken as 0.9 and 0.4 respectively.

James Kennedy and Russell Eberhart also produced the binary version of the PSO algorithm (BPSO) so it can be used in the discrete search spaces [26]. The difference between the PSO and the BPSO approaches is the position vector of the particle, which is in the BPSO, is a binary one. The velocity update of the \( i \)th element in the \( r \)th particle has a relation with the probability of the particle’s position that has a value of 0 or 1. The position update in the BPSO algorithm can be done by using an extra variable named as Sigmoid Limiting Transformation (SLT) which can be calculated as in equation (12):

\[ S(V_{ri}^{m+1}) = \frac{1}{1-\exp(V_{ri}^{m+1})} \]

where \( S(V_{ri}^{m+1}) \) is the sigmoid function of the \( i \)th element in the \( r \)th particle.

Then the position of the particle can be updated after finding the sigmoid function as in equation (13)

\[ X_{ri}^{m+1} = \begin{cases} 1 & \text{if } H_{ri} < S(V_{ri}^{m+1}) \\ 0 & \text{otherwise} \end{cases} \]

where \( H_{ri} \) is a random number uniformly generated between \([0,1]\).

4. HYBRIDIZATION OF THE QUANTUM COMPUTING WITH THE BPSO ALGORITHM

The quantum bit or the qubit is recognized as the smallest unit of the information that will be saved in a two-state quantum computer [27]. The qubit may take \( (0) \) state or \( (1) \) state that can be reshaped as \([0]\) and \([1]\) respectively or another state that produced from the superposition of the last states. The state of the qubit may be characterized as in equation (14)

\[ |\Psi\rangle = \alpha |0\rangle + \beta |1\rangle \]

where \((\alpha, \beta)\) are the complex numbers that identify the probability of amplitude for relative conditions and \( \alpha^2 \) equals zero and \( \beta^2 \) equals 1. Normalizing the quantum bit state to unity that ensures \( |\alpha|^2 + |\beta|^2 = 1 \). The state of the qubit can be modified by using the quantum gates. Examples of the quantum gates are the controlled-NOT gate, rotation gate, Hadamard gate and the NOT gate [28]. Kim and Han have been introduced a novel Quantum Evolutionary Algorithm (QEA) that is inspired by quantum computing [27]. The QEA characterization as the EAs that have individuals, population dynamics and evaluation function but QEA utilizes the probabilistic representation for the qubit. As a result of QEA, a major advantage has been approached which is the individual of the quantum bits which is a string of qubits and it has the representation of binary solutions in the search space. The individual of a qubit can be represented by a pair of numbers \( \alpha \) and \( \beta \) that can be described as a group of \((n)\) qubits such as in the following equation:
\[ q = \begin{bmatrix} |\alpha_1| & |\alpha_2| & \cdots & |\alpha_n| \\ |\beta_1| & |\beta_2| & \cdots & |\beta_n| \end{bmatrix} \]  

(15)

where \(|\alpha_i|^2 + |\beta_i|^2 = 1\) and \(i = 1, 2 \ldots n\).

The rotation gate is used to update the qubit of the individuals, which is represented by the following equation:

\[
(\Delta \theta_i) = \begin{bmatrix} \cos(\Delta \theta_i) - \sin(\Delta \theta_i) \\ \sin(\Delta \theta_i) \cos(\Delta \theta_i) \end{bmatrix}
\]  

(16)

where \(\Delta \theta_i\) is the jth qubit rotation angle that goes to 0 or 1 state. A predetermined lookup table is used to determine the value of \(\Delta \theta_i\) and adjusted as \(\theta_1 = 0, \theta_2 = 0, \theta_3 = 0.01\pi, \theta_4 = 0, \theta_5 = -0.01\pi, \theta_6 = 0, \theta_7 = 0, \theta_8 = 0\) and \(B\) is the best solution where \(B = (b_1, b_2, b_3, \ldots, b_n)\) [27].

In reference [19], a new approach has been suggested which is the Binary Particle Swarm Optimization inspired by Quantum Computing (QBPSO). The velocity of particles is updated in the BPSO by quantum computing. In the QBPSO, the probability \(|\alpha|^2 + |\beta|^2 = 1\) that makes the elements of particles get a state 0 or 1 and leads to the fact the velocity update in equation (9) is replaced by using quantum computing. Also, the inertia factor \(\omega\) and the factors \((c_1, c_2)\) of QBPSO are omitted and replaced by the rotation angle. The stored probability \(|\beta|^2\) in the \(rth\) qubit individual is used for updating the \(rth\) particle position vector and hence the \(ith\) element of \(rth\) particle gets a value 1 or 0 as in the equation (17).

\[
X_{ri}^{m+1} = \begin{cases} 
1 & \text{if } H_{ri} < |\beta_{ri}|^2 \\
0 & \text{otherwise}
\end{cases}
\]  

(17)

where \(r = 1, 2, 3, \ldots\) number of population, \(i = 1, 2, 3, \ldots\) number of elements and \(H_{ri}\) is a random number distributed uniformly between zero and 1.

**Table 1.** Lookup table for determining the rotation angle.

| \(x_i\) | \(b_i\) | Fitness (X) \(\geq\) Fitness (B) | \(\Delta \theta_i\) |
|----------|----------|-------------------------------|------------------|
| 0        | 0        | False                         | \(\theta_1\)     |
| 0        | 0        | True                          | \(\theta_2\)     |
| 0        | 1        | False                         | \(\theta_3\)     |
| 0        | 1        | True                          | \(\theta_4\)     |
| 1        | 0        | False                         | \(\theta_5\)     |
| 1        | 0        | True                          | \(\theta_6\)     |
| 1        | 1        | False                         | \(\theta_7\)     |
| 1        | 1        | True                          | \(\theta_8\)     |

An enhancement is performed to the rotation gate that updates the individuals of the qubit and resulted from this enhancement that the predefined lookup table will not be used for rotation angle determination [19]. Alternatively, \(P_{\text{best}}\) and \(G_{\text{best}}\) are used to update the rotation angle as in the equation (18):

\[
\Delta \theta_{ri} = \theta \times (y_{1r} \times (x_i^{G} - x_i^{P}) + y_{2r} \times (x_i^{P} - x_i^{r}))
\]  

(18)

where \(\theta\) is the rotation angle magnitude, \((x_i^{P}, x_i^{G})\) are the local and the global best positions and \((y_{1r}, y_{2r})\) are determined by the following equations:

\[
y_{1r} = \begin{cases} 
0 & \text{if } \text{Fitness of } (X_r) \geq \text{Fitness}(P_{\text{best}}) \\
1 & \text{otherwise}
\end{cases}
\]  

(19)
\[ \gamma_{2r} = \begin{cases} 0 & \text{if } \text{Fitness}(X_r) \geq \text{Fitness(Gbest)} \\ 1 & \text{otherwise} \end{cases} \quad (20) \]

The magnitude of the rotation angle is monotonously decreased from \( \theta_{\text{max}} \) to \( \theta_{\text{min}} \) with the iterations as in equation (21):

\[ \theta = \theta_{\text{max}} - \frac{\theta_{\text{max}} - \theta_{\text{min}}}{\text{iter}_\text{max}} \times m \quad (21) \]

5. LOCAL ATTRACTING IMPROVEMENT FOR QPSO ALGORITHM

In order to illustrate the local attracting concept, another topic must be explained and that is the quantum angle. Keeping in mind the normalization condition \( |\alpha|^2 + |\beta|^2 = 1 \), the quantum angle can be stated by the following equation:

\[ q_{ri}^m = \begin{bmatrix} \alpha_{ri}^m \\ \beta_{ri}^m \end{bmatrix} \text{ yields } \theta_{ri}^m : \begin{aligned} \left| q_{ri}^m \rightangle &= \cos \theta_{ri}^m |0\rangle + \sin \theta_{ri}^m |1\rangle \\ \theta_{ri}^m &= \arctan \frac{\alpha_{ri}^m}{\beta_{ri}^m} \end{aligned} \quad (22) \]

As a result, the quantum angle defines the qubit. Thus, the population of the quantum bit particles can be explained in the quantum angle format:

\[ q_r^m = \begin{bmatrix} q_{r1}^m, q_{r2}^m, q_{r3}^m, \ldots, q_{rk}^m \end{bmatrix}, Q(m) = \begin{bmatrix} q_{r1}^m, q_{r2}^m, q_{r3}^m, \ldots, q_{rk}^m \end{bmatrix} \]
\[ \theta_r^m = \begin{bmatrix} \theta_{r1}^m, \theta_{r2}^m, \theta_{r3}^m, \ldots, \theta_{rk}^m \end{bmatrix}, \theta(m) = \begin{bmatrix} \theta_{r1}^m, \theta_{r2}^m, \theta_{r3}^m, \ldots, \theta_{rk}^m \end{bmatrix} \]

Also, the quantum angle operator can replace the quantum rotation gate:

\[ \begin{bmatrix} \alpha_{ri}^{m+1} \\ \beta_{ri}^{m+1} \end{bmatrix} = \begin{bmatrix} \cos(\Delta \theta_{ri}^m) & -\sin(\Delta \theta_{ri}^m) \\ \sin(\Delta \theta_{ri}^m) & \cos(\Delta \theta_{ri}^m) \end{bmatrix} \begin{bmatrix} \alpha_{ri}^m \\ \beta_{ri}^m \end{bmatrix} \quad (23) \]

And that leads to

\[ \theta_{ri}^{m+1} = \Delta \theta_{ri}^m + \theta_{ri}^m \quad (24) \]

Consequently, we can conclude that the quantum angle is an angle vector in a complex vector space having two dimensions as illustrated in Figure (1) [23].

![Figure 1. Quantum angle.](image)

The individuals in the PSO algorithm fly randomly in the search space and update the velocity of them with a constant rate according to the experience of each individual and the experience of its neighbouring individuals. A trajectory analysis to discuss the convergence of a PSO algorithm has been made by Kennedy and Clerc [29]. The analysis reveals that the convergence to the solution is
achieved when the individual in the swarm approaches to its local attractor \( P_{r}^{m} = [P_{r1}^{m}, P_{r2}^{m}, P_{r3}^{m}, \ldots, P_{rk}^{m}] \) as it flies in the real search space which equals
\[
P_{r1}^{m} = r_{n}^{m} \cdot P_{best_{r1}}^{m} + (1 - r_{n}^{m}) \cdot G_{best_{r1}}^{m}
\] (25)

where \( r_{n}^{m} \) is a random number distributed uniformly between zero and 1.

Sun et al. have been proposed a crossover process as in the genetic algorithm to reproduce the local attractor because the local attractor found in the equation (30) cannot be generated in discrete binary search spaces [30]. Two offspring are selected randomly which are generated from the application of a crossover operation on the parents \( P_{best_{r}}^{m} \) and \( G_{best_{r}}^{m} \). The local attractor of binary search space is represented as in the equation (26) [23]:
\[
P_{r1}^{m} = \lambda_{r1}^{m} \cdot P_{best_{r1}}^{m} + (1 - \lambda_{r1}^{m}) \cdot G_{best_{r1}}^{m}
\] (26)

where \( \lambda_{r1}^{m} \) is a uniformly distributed random integer number between zero and 1. As it can be seen from equation (26), the position of the point \( P_{r}^{m} \) lies between \( P_{best_{r}}^{m} \) and \( G_{best_{r}}^{m} \) in the binary spaces. In the LAQBPSO algorithm, the quantum angle is used to encode the quantum bit and all the quantum bit particles in the population are regarded as a swarm of quantum angles.

In the LAQPSO algorithm, the initial value of each quantum angle is \( (\frac{\pi}{4}) \). The state value of the quantum bit defines depending on the probabilities of either \( (\alpha^{2} = 0) \) or \( (\beta^{2} = 1) \) and it can be described by the following equation:
\[
x_{r}^{m+1} = \begin{cases} 0 & \text{if } \, r_{n} < |\cos(\theta_{r1}^{m})|^{2} \\ 1 & \text{otherwise} \end{cases}
\] (27)

where \( r_{n} \) is a random number distributed uniformly between zero and 1.

As a result of equation (27), a binary string \( x_{r}^{m} = [x_{r1}^{m}, x_{r2}^{m}, x_{r3}^{m}, \ldots, x_{rk}^{m}] \) in the length of \( k \) that is being produced from the transformation of the \( rth \) particle \( \theta_{r}^{m} \) and the fitness value can be evaluated for each particle so as to find the values of \( P_{best} \) and \( G_{best} \).

The rotation gate is used to update the quantum angle depending on the rotation angle obtained from the local attractor. The rotation angle direction can be determined from using the local attractor and individuals of the current swarm as in the following equation:
\[
DIR(\theta_{r1}^{m}) = P_{r1}^{m} - X_{r1}^{m}
\] (28)

Depending on equation (27) the local attractor can be obtained with probability 100% if the initial value of \( \Phi_{r1}^{m} \) is taken in the range of \([0, \frac{\pi}{2}]\) that means \( P_{r1}^{m} \) equals 0 or 1. Therefore, the value of the quantum angle is equal to \( (\frac{\pi}{2}) \) or 0 and the value of \( \Phi_{r1}^{m} \) can be described as in equation (29):
\[
\Phi_{r1}^{m} = \frac{\pi}{2} \cdot P_{r1}^{m}
\] (29)

After that, the current quantum angle \( \theta_{r1}^{m} \) and \( \Phi_{r1}^{m} \) can be used to obtain the rotation angle magnitude as represented in the equation (30):
\[
|\Delta\theta_{r1}^{m}| = a \cdot | \Phi_{r1}^{m} - \theta_{r1}^{m} | \cdot r_{n}
\] (30)

where \( a \) is called a contraction factor and its importance for adjusting the rotation angle magnitude. Finally, the rotation angle can be described as in the following equation:
\[
\Delta\theta_{r1}^{m} = DIR(\theta_{r1}^{m}).|\Delta\theta_{r1}^{m}|
\] (31)
And the quantum angles of the swarm are updated using the equation (24).

6. SIMULATION AND RESULTS
The proposed algorithm in this paper was simulated using MATLAB R2017b environment to find a solution to the unit commitment dilemma. The computer that has been used has the following features: Core i5 CPU with a frequency of 2.4 GHz and RAM 4 GB. The LAQPSO algorithm is applied to a power system that consists of 10 thermal generation units with 10% spinning reserve for a time horizon 24 hours [20]. Table 2 represents the demand for 24 hours and Table 3 represents the parameters of the generators.

| Hour | Demand (MW) | Hour | Demand (MW) |
|------|-------------|------|-------------|
| 1    | 700         | 13   | 1400        |
| 2    | 750         | 14   | 1300        |
| 3    | 850         | 15   | 1200        |
| 4    | 950         | 16   | 1050        |
| 5    | 1000        | 17   | 1000        |
| 6    | 1100        | 18   | 1100        |
| 7    | 1150        | 19   | 1200        |
| 8    | 1200        | 20   | 1400        |
| 9    | 1300        | 21   | 1300        |
| 10   | 1400        | 22   | 1100        |
| 11   | 1450        | 23   | 900         |
| 12   | 1500        | 24   | 800         |

The initial value of the rotation angle in the LAQPSO algorithm was adjusted equal to \((\frac{\pi}{4})\) and the contraction coefficient is taken equal to 1, where it is in the range from 0.1 to 1. The population number is adjusted to 40 and the maximum number of iterations is equal to 25.

| Unit | a ($/h) | b ($/MWh) | c ($/MWh^2) | P_{min} (MW) | P_{min} (MW) | MUT (h) | MDT (h) | HSC ($) | CSC ($) | CSH (h) | Ini. state (h) |
|------|---------|-----------|-------------|--------------|--------------|---------|---------|--------|--------|--------|-------------|
| 1    | 1000    | 16.9      | 0.00048     | 455          | 150          | 8       | 8       | 4500   | 9000   | 5      | 8           |
| 2    | 970     | 17.26     | 0.00031     | 455          | 150          | 8       | 8       | 5000   | 10000  | 5      | 8           |
| 3    | 700     | 16.60     | 0.002       | 130          | 20           | 5       | 5       | 550    | 1100   | 4      | -5          |
| 4    | 680     | 16.50     | 0.00111     | 130          | 20           | 5       | 5       | 560    | 1120   | 4      | -5          |
| 5    | 450     | 19.70     | 0.00398     | 162          | 25           | 6       | 6       | 900    | 1800   | 4      | -6          |
| 6    | 370     | 22.26     | 0.00712     | 80           | 20           | 3       | 3       | 170    | 340    | 2      | -3          |
| 7    | 480     | 27.74     | 0.00079     | 85           | 25           | 3       | 3       | 260    | 520    | 2      | -3          |
| 8    | 660     | 25.92     | 0.00413     | 55           | 10           | 1       | 1       | 30     | 60     | 0      | -1          |
| 9    | 665     | 27.27     | 0.00222     | 55           | 10           | 1       | 1       | 30     | 60     | 0      | -1          |
| 10   | 670     | 27.79     | 0.00173     | 55           | 10           | 1       | 1       | 30     | 60     | 0      | -1          |

The total operation cost of the UC problem that solved with the LAQPSO algorithm is compared with several optimization methods as listed in Table 4.
Table 4. Total cost that produced by the LAQPSO and different approaches.

| Approach         | Total Cost ($) |
|------------------|----------------|
| LR [8]           | 565673         |
| PL [9]           | 564835         |
| GA [12]          | 566404         |
| BPSO [13]        | 565804         |
| IPSO [16]        | 563954         |
| ACSA [18]        | 564,049        |
| QBPSO [19]       | 563977         |
| QOTLB [22]       | 564394         |
| PSO-GWO [2]      | 565210         |
| Proposed algorithm| 563937         |
| LAQPSO           |                |

Table 5. Output power of the generators in the 10-units simulation system.

| Hour | U (1) | U (2) | U (3) | U (4) | U (5) | U (6) | U (7) | U (8) | U (9) | U (10) | Demand | Reserve |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|--------|---------|
|      | 455   | 245   | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 700    | 210    |
| 2    | 455   | 295   | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 750    | 160    |
| 3    | 455   | 370   | 0     | 0     | 25    | 0     | 0     | 0     | 0     | 850    | 247    |
| 4    | 455   | 455   | 0     | 0     | 40    | 0     | 0     | 0     | 0     | 950    | 122    |
| 5    | 455   | 390   | 0     | 130   | 25    | 0     | 0     | 0     | 0     | 1000   | 202    |
| 6    | 455   | 360   | 130   | 130   | 25    | 0     | 0     | 0     | 0     | 1100   | 232    |
| 7    | 455   | 410   | 130   | 130   | 25    | 0     | 0     | 0     | 0     | 1150   | 182    |
| 8    | 455   | 455   | 130   | 130   | 30    | 0     | 0     | 0     | 0     | 1200   | 132    |
| 9    | 455   | 455   | 130   | 130   | 85    | 20    | 25    | 0     | 0     | 1300   | 197    |
| 10   | 455   | 455   | 130   | 130   | 161.95| 33.05 | 25    | 10    | 0     | 1400   | 152    |
| 11   | 455   | 455   | 130   | 130   | 162   | 73    | 25    | 10    | 10    | 1450   | 157    |
| 12   | 455   | 455   | 130   | 130   | 162   | 80    | 25.11 | 42.89 | 10    | 10     | 1500   | 162    |
| 13   | 455   | 455   | 130   | 130   | 162   | 33    | 25    | 10    | 0     | 1400   | 152    |
| 14   | 455   | 455   | 130   | 130   | 85    | 20    | 25    | 0     | 0     | 1300   | 197    |
| 15   | 455   | 455   | 130   | 130   | 30    | 0     | 0     | 0     | 0     | 1200   | 132    |
| 16   | 455   | 310   | 130   | 130   | 25    | 0     | 0     | 0     | 0     | 1050   | 277    |
| 17   | 455   | 260   | 130   | 130   | 25    | 0     | 0     | 0     | 0     | 1000   | 332    |
| 18   | 455   | 360   | 130   | 130   | 25    | 0     | 0     | 0     | 0     | 1100   | 232    |
| 19   | 455   | 455   | 130   | 130   | 30    | 0     | 0     | 0     | 0     | 1200   | 132    |
| 20   | 455   | 455   | 130   | 130   | 161   | 33    | 25    | 10    | 0     | 1400   | 152    |
| 21   | 455   | 455   | 130   | 130   | 85    | 20    | 25    | 0     | 0     | 1300   | 197    |
| 22   | 455   | 455   | 0     | 0     | 144.94| 20.06 | 25    | 0     | 0     | 1100   | 137    |
| 23   | 455   | 425   | 0     | 0     | 0     | 20    | 0     | 0     | 0     | 900    | 90     |
| 24   | 455   | 345   | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 800    | 110    |

TOTAL OPERATION COST = 563937 $
Table 4 shows the total operation cost of UC problem is decreased by using LAQPSO algorithm in comparison with the literary works. Table 5 displays the generated power for each unit every hour.

In this paper, the total start-up and fuel costs have the specified values of 4090$ and 559847$ respectively. The condition of 10% spinning reserve is fulfilled at each hour as well as the other condition such as the minimum downtime and minimum uptime, maximum and minimum power.

7. CONCLUSION
This paper proposes a hybrid LAQPSO algorithm to solve the problem of unit commitment. The proposed algorithm incorporates quantum computing and the PSO algorithm with a local attractor to form a hybrid algorithm (LAQPSO). This hybrid way helped the PSO algorithm to overcome the disadvantages such as lower convergence speed and trapping in local minimum solution. A 10-unit power system is utilized to validate the effectiveness of the proposed LAQPSO algorithm. The results showed that the LAQPSO algorithm is robust and has a better convergence to the solution. Also, it achieved all the constraints of the UC problem and increased the savings compared with different techniques in the literature.

8. REFERENCES

[1] Wood AJ, Wollenberg BF, Sheblé GB. Power generation, operation, and control. third. Hoboken, New Jersey: John Wiley & Sons, Inc.; 2014. pp 147–186.

[2] Kamboj VK. A novel hybrid PSO--GWO approach for unit commitment problem. Neural Comput Appl [Internet]. 2016 Aug;27(6):1643–55. Available from: https://doi.org/10.1007/s00521-015-1962-4

[3] Hobbs BF, Rothkopf MH, O’Neill RP, Chao H. The next generation of electric power unit commitment models. Springer Science& Business Media, llc; 2001.

[4] Rajan CCA, Mohan MR, Manivannan K. Neural-based tabu search method for solving unit commitment problem. IEE Proc - Gener Transm Distrib. 2003;150(4):469–74.

[5] Singhal PK, Sharma RN. Dynamic programming approach for solving power generating unit commitment problem. In: 2011 2nd International Conference on Computer and Communication Technology. ICCCT-2011. Allahabad; 2011. p. 298-303.

[6] Cohen AI, Yoshimura M. A Branch-and-Bound Algorithm for Unit Commitment. IEEE Power Eng Rev [Internet]. 1983 Feb [cited 2019 Jul 23];PER-3(2):34–5. Available from: http://ieeexplore.ieee.org/document/5519636/

[7] Palis D, Palis S. Efficient Unit Commitment-A modified branch-and-bound approach. In: IEEE Region 10 Annual International Conference, Proceedings/TENCON. Singapore; 2017. p. 267–71.

[8] Singhal PK. Generation scheduling methodology for thermal units using lagrangian relaxation. In: 2011 Nirma University International Conference on Engineering: Current Trends in Technology, NUiCONE 2011 - Conference Proceedings. Ahmedabad, Gujarat; 2011. p. 1–6.

[9] Elsayed AM, Maklad AM, Farrag SM. A new priority list unit commitment method for large-scale power systems. In: 2017 19th International Middle-East Power Systems Conference, MEPCON 2017 - Proceedings. Cairo; 2018. p. 359–67.

[10] Chang GW, Tsai YD, Lai CY, Chung JS. A practical mixed integer linear programming based approach for unit commitment. In Denver, Denver; 2005. p. 221-225 Vol.1.

[11] Hu G, Yang L. The parallel interior point for solving the continuous optimization problem of unit commitment. In: Proceedings - 2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI ,Datong .2016. Datong; p. 1333–8.

[12] Damousis IG, Bakirtzis AG, Dokopoulos PS. A solution to the unit-commitment problem using integer-coded genetic algorithm. IEEE Trans Power Syst. 2004;19(2):1165–72.

[13] Zwe-Lee Gaing. Discrete particle swarm optimization algorithm for unit commitment. In: 2003 IEEE Power Engineering Society General Meeting (IEEE Cat No03CH37491), Toronto, Ont., 2003. p. 418–24.
[14] Lang J, Tang L, Zhang Z. An Improved Binary Particle Swarm Optimization for Unit Commitment Problem. In: 2010 Asia-Pacific Power and Energy Engineering Conference, Chengdu [Internet]. Chengdu: IEEE; 2010 [cited 2019 Jul 24]. p. 1–4. Available from: http://ieeexplore.ieee.org/document/5448417/

[15] Chandrasekaran K, Simon SP. Binary/real coded particle swarm optimization for unit commitment problem. In: 2012 International Conference on Power, Signals, Controls and Computation, EPSCICON, Thrissur, Kerala,. 2012. p. 1–6.

[16] Zhao B, Guo CX, Bai BR, Cao YJ. An improved particle swarm optimization algorithm for unit commitment. Int J Electr Power Energy Syst [Internet]. 2006 Sep 1 [cited 2019 Jul 24];28(7):482–90. Available from: https://www.sciencedirect.com/science/article/pii/S014206150600055X

[17] Simopoulos DN, Kavatza SD, Vournas CD. Unit commitment by an enhanced simulated annealing algorithm. In: IEEE Transactions on Power Systems. p. 68–76, 2006.

[18] Sun-im T, Ongsakul W. Ant colony search algorithm for unit commitment. In: IEEE International Conference on Industrial Technology, 2003, Maribor, Slovenia, 2003. p. 72–7.

[19] Jeong YW, Park JB, Jang SH, Lee KY. A new quantum-inspired binary PSO for thermal unit commitment problems. In: 2009 15th International Conference on Intelligent System Applications to Power Systems, Curitiba, Curitiba, Brazil; 2009. p. 1–6.

[20] Jeong YW, Park JB, Jang SH, Lee KY. A new quantum-inspired binary PSO: Application to unit commitment problems for power systems. IEEE Trans Power Syst. 2010 Aug;25(3):1486–95.

[21] Zeynal H, Hui LX, Jiazhen Y, Eidiani M, Azzopardi B. Improving Lagrangian Relaxation unit commitment with Cuckoo Search Algorithm. In: Conference Proceeding - 2014 IEEE International Conference on Power and Energy, PECon, Kuching. 2014. 2014. p. 77–82.

[22] Roy PK, Sarkar R. Solution of unit commitment problem using quasi-oppositional teaching learning based algorithm. Int J Electr Power Energy Syst [Internet]. 2014 Sep 1 [cited 2019 Jul 25];60:96–106. Available from: https://www.sciencedirect.com/science/article/pii/S0142061514000714

[23] Shao D, Hu S, Fei Y. A new quantum particle swarm optimization algorithm with local attracting. Neural Netw World. 2016;26(5):477–96.

[24] Zhu J. Optimization of Power System Operation. 1st ed. Optimization of Power System Operation. Hoboken, New Jersey: John Wiley & Sons, Inc.; 2008. 1–603 p.

[25] Kennedy J, Eberhart R. Particle swarm optimization. In: Proceedings of ICNN’95 - International Conference on Neural Networks, Perth, WA, Australia. 1995. p. 1942–8.

[26] Kennedy J, Eberhart RC. A discrete binary version of the particle swarm algorithm. In: 1997 IEEE International Conference on Systems, Man, and Cybernetics Computational Cybernetics and Simulation, Orlando, FL, USA. 1997. p. 4104–8.

[27] Han KH, Kim JH. Quantum-inspired evolutionary algorithm for a class of combinatorial optimization. IEEE Trans Evol Comput. 2002 Dec;6(6):580–93.

[28] Hey T. Quantum computing: an introduction. Computing & Control Engineering Journal [Internet]. 1999 Jun [cited 2019 Jul 28];10(3):105–12. Available from: https://digital-library.theiet.org/content/journals/10.1049/cce_19990303

[29] Clerc M, Kennedy J. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. In: IEEE Transactions on Evolutionary Computation. p. 58–73, Feb. 2002.

[30] Sun J, Xu W, Fang W, Chai Z. Quantum-Behaved Particle Swarm Optimization with Binary Encoding. In: Beliczynski B, Dzielinski A, Iwanowski M, Ribeiro B, editors. Adaptive and Natural Computing Algorithms, LNCS Berlin: Springer,. Berlin, Heidelberg: Springer Berlin Heidelberg; 2007. p. 376–85.