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Quantum Inspired Evolutionary Algorithm with a Novel Elitist Local Search Method for Scheduling of Thermal Units

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Abstract— the unit commitment problem is a complex and essential problem in the power generation field, which is solved to obtain the schedule of a large number of generating units to minimize the operating cost and the fulfillment of consumer load demand. The present work solves the unit commitment problem using quantum-inspired evolutionary algorithms with a novel elitist local search method (QIEA-ELS). The proposed algorithm solves the unit commitment problem efficiently and its applicability is verified on various unit test systems. The constraints are satisfied efficiently to find a feasible solution, the novel elitist search method is used to locally explore the search area around the fittest individual to find a better solution in its vicinity in genotype space represent by qubits. The solution of the unit commitment is carried out considering two small population sizes as suggested in earlier work by other authors using QIEA, though it can be extended using larger population size also. The computational time is also reduced by using the suggested method with a novel elitist local search (ELS) method. The results obtained after applying the proposed algorithm are found to better as compared to other well-known solution techniques.

Keywords- Unit commitment problem, constraints, thermal unit, QIEA, evolutionary algorithms, repair-based constraint handling method.

NOMENCLATURE

T	number of hours	Min_J^{UPTIME}	Min. Uptime of jth unit
K	number of generating units	C_J^t	Time of cold start of jth unit
t	Time interval (t=1,2,3…. T)	SPR^t	Spinning reserve at tth hour
$F(PG_j^t)$	The function of fuel cost of jth unit at tth hour	PG_j^{MAX}	Max. Power generation bounds of jth unit
SU_j^{cost}	The unit start cost for jth unit	PG_j^{MIN}	Min. Power generation bounds of jth unit
SD_j^{cost}	Unit shutdown cost for jth unit	TON_J^t	Continuously ON time of jth unit till tth time
G_j^t	Status of thermal unit (1= ON; 0= OFF)	$TOFF_J^t$	Continuously OFF time of jth unit till tth time
x_J, y_J, z_J	Coefficient of the fuel cost function	PG_{DEMAND}^t	Power demand of consumers at tth hour
S_J^{HOT}	starting cost of jth unit (Hot start)	j	Unit index (j=1,2,3…. k)
S_J^{COLD}	starting cost of jth unit (cold start)	PG_j^t	Power generation from jth unit at tth hour
$Min_J^{DOWNTIME}$	Min. downtime of jth unit		

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I. INTRODUCTION

The demand of consumers for electrical power is increasing each year rapidly. The fulfillment of this bulk demand for electrical energy is a difficult task for power-generating utilities. A large number of new power-generating units are installed every year worldwide to meet the load demand of the consumer. Different kinds of generating units, and energy sources like solar power plants, nuclear power plants, wind power plants, hydropower plants, geothermal power plants, etc. are invented, developed, and used for power generation in the last two centuries. Coal-fired thermal units have still a large share in power generation among all the power-generating units in the entire world. The operation and scheduling of a large number of coal-based thermal power plants is a laborious task. The setting up of a large number of generating units in a well-arranged sequence to achieve the load demand at the lowest cost is known as Unit Commitment (UC). The solution of a Unit Commitment Problem (UCP) is a complex and challenging task for the utilities. The prime target of UCP is the setting up of generating units along with cost minimization.

Large numbers of solution methods and solution techniques are suggested today to solve the unit commitment problem. All these techniques are invented and developed in different periods by various researchers to solve optimization problems. The work in [1-5] provide the development of various solution methods, unit commitment problem formation, and historical study of the UCP during different period of time. A detailed survey on unit commitment is suggested in [1] along with its solution techniques. A comprehensive study of UCP literature is given in [2] regarding the various reputed work in the field of UCP. A comparative study of various solution methods is suggested in [3] along with a detailed study of UCP. The various kinds of solution techniques discussed in detail [4-5] are used to solve the UCP in various works. A combined approach of the modified priority list (MPL) method and the sequential approach with matrix framework (SAMF) are used to solve the UCP [6] along with the economic dispatch approach for thermal units. The suggested approach was also verified on different unit test cases and provided improved results. A genetic algorithm (GA) is used to solve the UCP for thermal power-generating units. All the constraints of the system are satisfied with achieving minimized cost of generation. The results of the suggested algorithms provide improved convergence and enhanced solution quality [7].

A UCP for thermal units is carried out using the benders decomposition techniques [8]. The UCP is solved by providing efficient scheduling for the thermal units and constraint satisfaction. The suggested method segregated the problem into master and subproblems. The results prove the efficiency of the suggested algorithm. thermal UCP is solved using the mixed integer linear programming method (MILP) [9]. The search space is reduced in the current work using a tight and compact formation. The test results are found effectively by evaluating the suggested algorithm on the different unit test cases. A modified shuffled frog leaping (MSFL) algorithm is utilized [10] to carry out a thermal Unit commitment problem (TUCP) with a cost minimization objective under a constrained environment. The obtained results are compared with other well-known techniques and found satisfactory. A feasible modified sub-gradient (FMSG) technique is used to carry out a TUCP [11]. The current approach does not work to find global minima (unconstrained) for a lagrangian function. The suggested approach was employed on a real thermal power plant in turkey to evaluate the suggested technique. A multi-agent fuzzy reinforcement learning task is cast and used for the solution of a TUCP [12]. The suggested approach does not consider any kind of initial assumption to carry out the work. The result proves the effectiveness of the method to carry out TUCP. A MILP is used [13] similar to [9] for determining the solution of a TUCP. The UCP is a mixed inter problem so, it requires real and binary variables to carry out the problem.

Unit commitment problem is generally solved for a 24-hour duration divided into different spans (15 minutes or 30 minutes). Some work solves the UCP for a few hours (below 24 hours) called the short-term unit commitment problem (STUCP) and some researchers solve the UCP for the long term which is called the long-term unit commitment problem (LTUCP). A similar approach to solving long-term UCP is adopted in [14-15]. The work suggested in [14] solves the UCP for a week and the work proposed in [15] solves a month-long unit commitment problem. A deterministic UCP is solved using mixed integer quadratic programming (MIQP) [16]. The binary variables and mathematical programming is used in this work. The results obtained are found satisfactory. Some work solves UCP by dividing it into small sub-problems, or a sequence of problems to solve the UCP in multiple stages. The work suggested in [17] divides the unit commitment problem into a master and a sub-problem. The suggested work solves the problem using the Lagrangian relaxation (LR) method. A TUCP is solved [18] using a binary firework algorithm (BFWA). The various constraints are gratified during the search for optimal results. The suggested approach was tested on different unit test cases (10-100). The results describe the quality of the BFWA to solve the UC problem. Similarly, a UCP is solved using GA, fuzzy logic (FL), and priority list (PL) [19] for STUCP.

The unit commitment model may be formed by considering different cost functions, constraints, objectives, and other researchers' choice-based parameters. The work suggested in [6-19] solved the deterministic unit commitment problem (DUCP) model. The work suggested in [20-21] solves the UCP in a deregulated environment. A UCP is solved using particle swarm optimization (PSO) in the deregulated environment [20]. A similar approach is adopted in [21] to solve a UCP using a MILP. Constraints are an essential part of the unit commitment problem that must be satisfied during the search for an optimal feasible solution. Some special constraints are also used in the

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solution of the UCP like fuel constraints, security constraints, etc. Similarly, a fuel constraint is used in the [22] in UCP and solved using the LR method. The large-scale unit commitment problem is a difficult task to solve. On the large scale, the unit commitment problem is commonly solved for 100 or more units in most large-scale unit commitment problems (LSUCP). An LSUCP is solved in [23] using MILP and a modified branch & bound (BB) method on a large number of units. The suggested approach was also tested on IEEE 118 bus system and 54 units. Security-constrained unit commitment problem (SCUCP) formed with reliability and security concerns. The work suggested in [24-25] solves a security SCUCP. The work suggested in [26-28] is based on the approach of profit maximization. This approach is known as a profit-based unit commitment problem (PBUCP). A unit commitment problem is solved using a quantum-inspired evolutionary algorithm [29] adopting a lambda-iteration method to solve the economic generation allocation issue. The suggested work uses two population sizes 4 and 18 with different generations (100, and 200). The obtained results are compared with a different solution technique and found impressive. The suggested algorithms are found capable to solve the UCP efficiently with less computational time and enhanced results.

Local search (LS) uses small memory space and consumes lesser time to explore a small area in the search space. LS methods are the techniques used to solve hard and complex optimization problems along with a global optimization technique. LS is performed to improve performance, improve the quality of the solution, increase the speed of the calculation, and explore the less crowded area to search for more feasible solutions. A strategy of levy flight is used as a local search technique to improve the capability of local search with the gravitational search algorithm [30]. The levy flight technique helps in the diversity improvement of swarms using the mutation process and enhances the convergence speed. A binary variant of hill climbing algorithms is utilized as a local search method to improve the exploitation along with using a new mutation process. The local search is performed with a binary differential evolution algorithm [31]. A local search method is used to search the adjacent scheduling for a feasible solution in a UC problem [32] A neighborhood search is performed along with an interior point search method to solve a hard UCP. The concept of neighborhood refers that can full fill the various constraints to find a feasible solution. A large search space is used in this work and takes the benefits of the interior point method to improve the speed of calculation [33] The economic load dispatch with emission reduction approach utilizes a local search method along with GA. The local search method is used as a neighborhood search engine for the improvement of the solution quality. LS explores the low crowded area in search of non-dominated solutions [34]. An adaptive LS method is used for exploitation purposes locally. in the beginning, the LS and global search (GS) are performed alternatively and the population size is reduced to one, but in the end stages, the LS is performed for the search of the last individuals [35]. An LS based on the Hadamard matrix is used to enhance the performance and improve searchability [36] with an enhanced probability of finding a feasible optimal solution. The new search method overcomes the limitation of the search process. LS is performed on six problem domains with enhanced performance and solution quality. The LS was designed based on an iterated evolutionary algorithm with a mutation operator and controlled the performance enhancement [37].

The study of the [1-29] provides us a valuable comprehensive knowledge of the UCP. The unit commitment model is generally solved for a 24-hour duration but it may be solved for a long duration (a week or a month). The unit commitment model may a solo objective or multiple objective problem. The various kinds of approaches like security, reliability, profit, cost, emission, etc. may be added as an objective or considered as a constraint in unit commitment problem formation. A large number of solution techniques are developed and used for the solution of the unit commitment problem, these algorithms may be categorized into different categories like nature-inspired algorithms, classical algorithms, and hybrid algorithms. Today nature-inspired evolutionary algorithms are widely used to solve various kinds of optimization problems. Evolutionary algorithms (EAs) are very trendy due to their easy implementation and fast computing capability to find a feasible solution. These algorithms have several advantages over the other conventional methods. But there are some issues that the EAs have to face like diversity issues, convergence issues, the balance between exploration and exploitation, etc. These algorithms are not able to make a difference between the objective function and the constraints. So, it becomes a necessity to adopt a constraint-handling technique to handle the constraints. The work suggested in [38-42] described the different constraint handling methods.

The present work uses the data of power-generating units from the work suggested in [29]. A Novel elitist local search (ELS) strategy is also used in the current work to improve the quality of the solution in [29]. The ELS is applied to the best feasible solution to enhance the quality level of the solution. This ELS approach is utilizing the eight-angle rotation strategy to improve the solution quality. An enhanced variant of the quantum-inspired evolutionary algorithm (QIEA) is used to carry out the present work. The current work is arranged further in various segments. The formation of the unit commitment problem is suggested in 2nd segment and the algorithm is described in 3rd segment. The effectiveness of the suggested method is evaluated in 4th segment with different unit test systems. Results are provided in the 5th segment and followed by the conclusion in the 6th segment.

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II. THERMAL UNIT COMMITMENT PROBLEM FORMATION

a. Objective function

The entire operating cost of thermal power generating units is modeled as shown in equation 1. It is considered as the addition of the fuel cost with the start-up cost, and shutdown cost of all the units.

$$T_{\text{cost}} = \sum_{t=1}^{T}\sum_{j=1}^{k}\left[F\left(PG_j^t\right) + SU_j^{\cos t}\left(1 - G_j^{t-1}\right)G_j^t + SD_j^{\cos t}G_j^{t-1}\left(1 - G_j^t\right)\right] \quad (1)$$

The fuel cost of the thermal units is explained in equation 2 as shown below:

$$F(PG_j^t(t)) = x_J + PG_j^t y_J + z_J(PG_j^t)^2 \quad (2)$$

The startup cost of the thermal power-producing units is calculated according to equation 3. The initial status of the unit has a direct impact on the startup cost. The hot start cost and cold start cost of the generating unit are calculated accordingly. The input data for the thermal unit along with various parameters are provided in table 1

$$SU_j^{\cos t} = \begin{cases} S_J^{HOT}; & Min_J^{DOWNTIME} \le TOFF_J^t \le Min_J^{DOWNTIME} + C_J^t \\ S_J^{COLD}; & TOFF_J^t \ge Min_J^{DOWNTIME} + C_J^t \end{cases} \quad (3)$$

b. CONSTRAINTS

1. CONSTRAINT FOR POWER DEMAND BALANCE:

All thermal units must generate the same amount of electricity, and customers' load demands must be equal. The constraint for the power demand balance is satisfied according to equation 4.

$$\sum_{i=1}^{K} G_j^t PG_j^t - PG_{DEMAND}^t = 0 \quad (4)$$

2. CONSTRAINT LIMIT FOR SPINNING RESERVE:

The availability of spinning reserves determines the system's dependability. The adequate reserves required are maintained according to equation 5 to meet the power loss due to unit failure or sudden demand increase.

$$\sum_{i=1}^{K} G_j^t\left(PG_j^{MAX} - PG_j^t\right) \ge SPR^t \quad (5)$$

3. UNIT POWER GENERATION CONSTRAINTS:

The power generation level of all the thermal units must remain between the maximum and minimum power generation limit as provided in equation 6 as per the capacity of the unit.

$$PG_j^{MAX} \le PG_j^t \le PG_j^{MIN} \quad (6)$$

4. CONSTRAINT LIMIT FOR MINIMUM UPTIME AND MINIMUM DOWNTIME FOR THE UNITS:

A particular thermal unit must respect the minimum uptime duration and minimum downtime limit for safe operation during its commitment and de-commitment operation.

$$\begin{cases} (TON_j^{t-1} - Min_J^{UPTIME})(G_j^{t-1} - G_j^t) \ge 0 \\ (TOFF_j^{t-1} - Min_J^{DOWNTIME})(G_j^t - G_j^{t-1}) \ge 0 \end{cases} \quad (7)$$

III. PROPOSED ALGORITHM

The EAs are based on the "biological evolution hypothesis of nature" proposed by Charles Darwin and Alfred Russel Wallace in 1858. The natural selection of individuals by nature from a large population and producing the next generation is a key factor of natural biological evolution. The fittest individual will survive and produce the next generation [43]. The evolutionary algorithms are based on this principle and are used to solve complex optimization problems. Evolutionary algorithms have several advantages over classical methods. These are stochastic search methods used to find the fittest individual. There are various operators used in EAs that operate on a large population in search of an optimal solution. These operators require some parameters that can influence the performance of the EAs. Although the EAs have proved themselves very effective in problem-solving and can provide the best possible solution. But these solution methods have some limitations. The key issues are diversity, premature convergence problems, parameter tuning requirements, local maxima, and blindness for constraints [44-45]. There is no assurance of convergence and the parameters of EAs require a proper value assignment process. The demand for a delicate balance between exploration and exploitation is also a key challenge in EAs. The algorithms may trap in local maxima and EAs cannot differentiate between objectives and constraints. EA requires a constraint handling technique to satisfy the constraint and achieve a feasible solution. The most common example of EAs is the genetic algorithms based on the “survival of the fittest” concept, inspired by the genetic evolution of the chromosomes. The present work is using an elitist local search (ELS) strategy to enhance the search process and quality of the solution along with QIEA. The QIEA is a population-based search algorithm inspired by the principles of quantum mechanics that represent individuals by quantum bit. A quantum bit (Qubit)is the smallest and prime unit of information in quantum computing. A qubit has a probabilistic nature and stores the information in two states under superimposed conditions. It stores the values in 0 and 1 but also considers the states between 0 and 1. Individuals can be represented by a string of qubits. QIEA is capable of finding better diversity and a fine balance between exploration and exploitation.

A. Qubit Representation

A qubit is the primary information unit in the quantum computing process. It is the smallest unit to store information. In the present work, two qubits are used instead of a single qubit. The qubit is equitant to a classical bit but the probabilistic nature of the qubit makes it superior to the classical bit. The qubit stores the value either in the state of 0 or 1. The probabilistic nature of qubit allows it to consider all the possible states between 0 and

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1. This ability of a qubit makes a big difference between a qubit and a classical bit [44-46]. A qubit may represent as shown in equation 8 in vector form of Hilbert Space with two states.

$$|\boldsymbol{\Psi}>= \boldsymbol{\alpha}|\mathbf{0}> +\boldsymbol{\beta}|\mathbf{1}> \qquad (8)$$

The $|\mathbf{0}>$and $|\mathbf{1}>$ represents 0 and 1 values respectively and the $|\boldsymbol{\alpha}|^2$and$|\boldsymbol{\beta}|^2$is the probability amplitude of the qubit for the two different states as $|\mathbf{0}>$and $|\mathbf{1}>$ with the below given states of affair should be satisfied:

$$|\alpha|^2+|\beta|^2=1 \qquad (9)$$

If the $|\boldsymbol{\beta}|^2$ is larger than larger its probability to occupy the 1 state and if $|\boldsymbol{\alpha}|^2$is larger than the probability of occupying a 0 state is higher. A string of n number of qubits may be represented as a qubit individual shown below:

$$\begin{vmatrix} \boldsymbol{\alpha 1} & \boldsymbol{\alpha 2} & \boldsymbol{\alpha 3} & \ldots\ldots\ldots\ldots & \boldsymbol{\alpha n} \\ \boldsymbol{\beta 1} & \boldsymbol{\beta 2} & \boldsymbol{\beta 3} & \ldots\ldots\ldots\ldots & \boldsymbol{\beta n} \end{vmatrix} \qquad (10)$$

The advantage of qubit representation is that it can be described as a linear superposition of the states. The n number of qubits can represent 2^n states at a time by utilizing the superposition principle and qubit representation. For example, suppose α and β have equal values that are equal to $\frac{1}{\sqrt{2}}$ than all possible states for linear superposition will be shown as:

$$|\boldsymbol{\Psi}>= \sum_{\mathbf{M=1}}^{\mathbf{2^n}} \frac{\mathbf{1}}{\sqrt{\mathbf{2^n}}}\Big|\mathbf{x_M}> \qquad (11)$$

Where X_n is the M^{th} state of and shown by a binary string. If the n is considered equal to two then four possible states of the two qubits are shown by equation 12.

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \qquad (12)$$

the linear superimposed states are shown in equation 13 in a matrix. It shows that the possible probability for each state is $\frac{1}{4}$ and the individual having two qubits possess four states at a similar time [29].

$$\frac{1}{2}|\mathbf{00}> +\frac{1}{2}|\mathbf{01}> +\frac{1}{2}|\mathbf{10}> +\frac{1}{2}|\mathbf{11}> \qquad (13)$$

Rotation Gate strategy: **g**ate rotation strategy is applied in this work to move the solution individuals towards the direction of finding fittest solution or attaining an optimal value. A quantum gate RG used as a variation operator in this work for the updating of the qubits. The updated qubit at any particular t^{th} generation must fulfill the equation 9. The rotation gates and updating methods is shown below

$$\mathbf{RG}(\Delta\,\theta_{ji}^t) = \begin{bmatrix} \mathbf{cos}(\Delta\,\theta_{ji}^t) & -\mathbf{Sin}(\Delta\,\theta_{ji}^t) \\ \mathbf{Sin}(\Delta\,\theta_{ji}^t) & \mathbf{cos}(\Delta\,\theta_{ji}^t) \end{bmatrix} \qquad (14)$$

$$\begin{bmatrix} \boldsymbol{\alpha}_{ji}^t \\ \boldsymbol{\beta}_{ji}^t \end{bmatrix} = \mathbf{RG}(\Delta\,\theta_{ji}^t)\begin{bmatrix} \boldsymbol{\alpha}_{ji}^{t-1} \\ \boldsymbol{\beta}_{ji}^{t-1} \end{bmatrix} \qquad (15)$$

Changes in rotational angle, as shown in figure 1, are what determine the direction and amplitude of rotation. The two controlling variables are, respectively, $\boldsymbol{x_j^t}$ and $\boldsymbol{b_j^t}$, which determine the optimal solution, $\boldsymbol{B^t}$, to the B(t) equation. The objective functions of the $\boldsymbol{X_j^t}$ and $\boldsymbol{B^t}$.are represented by $\boldsymbol{f}(\boldsymbol{X_j^t})$ greater than $\boldsymbol{f}(\boldsymbol{B^t})$, respectively. When. $\boldsymbol{f}(\boldsymbol{X_j^t})$ and $\boldsymbol{f}(\boldsymbol{B^t})$ the rotation angle is determined in one of two methods. The value of is adjusted to a positive number (+) such that the likelihood of obtaining state 1 rises if the qubit is located in the first and third quadrants as indicated in figure 1. The is assigned to a negative value if the qubit stays in the second and fourth quadrants, increasing the likelihood that state 1 will be reached.

B. Implementation of the Quantum-Inspired Evolutionary Algorithm with Elitist Local Search on Unit Commitment Problem

Q(t) is the group of Qubit initialized at t=0, and $\mathbf{Q(t)} = [\mathbf{q_1^t}, \mathbf{q_2^t}, \mathbf{q_3^t}, \ldots.. \mathbf{q_n^t}]$ is described as a group of large numbers of qubits arranges as a matrix formation. Where n is the population size of the Q(t). The Q(t) initialized with the same probability that is equal to $\frac{\mathbf{1}}{\sqrt{\mathbf{2}}}$.. here the $\mathbf{q_j^t}$ is defined as the jth qubit individual in the matrix at tth iteration number. The application of qubit in the UCP is given by N*H size matrix formation, here N is number of the power generating units and the H is scheduling hours (h= 1,2, 3, …H) [29,46].

$$q_j^t = \begin{bmatrix} q_{j11}^t & q_{j12}^t & q_{j13\ldots\ldots}^t & q_{jH}^t \\ \beta_{j11}^t & \beta_{j12}^t & \beta_{j13\ldots\ldots}^t & \beta_{jH}^t \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ q_{jN1}^t & q_{jN2}^t & q_{jN3\ldots\ldots}^t & q_{jNH}^t \\ \beta_{jN1}^t & \beta_{jN2}^t & \beta_{jN3\ldots\ldots}^t & \beta_{jNH}^t \end{bmatrix} \qquad (17)$$

X(t) is the set of solutions obtained by the observation of the $\boldsymbol{q_j^t}$. it is defined as a group of generating unit schedule $\boldsymbol{X}(\boldsymbol{t}) = [\boldsymbol{X_1^t} \quad \boldsymbol{X_2^t} \quad \ldots\ldots\ldots.\boldsymbol{X_n^t}]$. Every scheduling solution is a N*H matrix [29,46]. The matrix formation of $\boldsymbol{X_j^t}$ is provided in the equation 18.

$$\boldsymbol{X_j^t} = \begin{bmatrix} x_{j11}^t & x_{j12}^t & x_{j13\ldots\ldots}^t & x_{jH}^t \\ x_{j21}^t & x_{j22}^t & x_{j23\ldots\ldots}^t & x_{j2H}^t \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ x_{j(N-1)1}^t & x_{j(N-1)2}^t\, x_{j(N-1)3}^t & \cdots & x_{j(N-1)H}^t \\ x_{jN1}^t & x_{jN2}^t & x_{jN3\ldots\ldots}^t & x_{jNH}^t \end{bmatrix} \qquad (18)$$

B(t) is a matrix that is used to store the best obtained solutions in the entire population. in this storage process the local best solution obtained from the sub-populations are also considered.1

QIEA can be described by its representation of Qubit for population diversity. It is also described by its process of observation to make a binary solution from qubit individuals and the updating process for driving the individuals towards a better solution. The present work is utilizing an elitist local search

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method. In the Elitist Local Search Heuristic, the qubits associated with the best individuals are updated so that the best individual could be improved further by rotating the associated qubit by a small angle in the same direction to increase the probability of getting 0 or 1 as the case may be, which is not being done in the rotation strategy employed by QIEA implementation in [29].

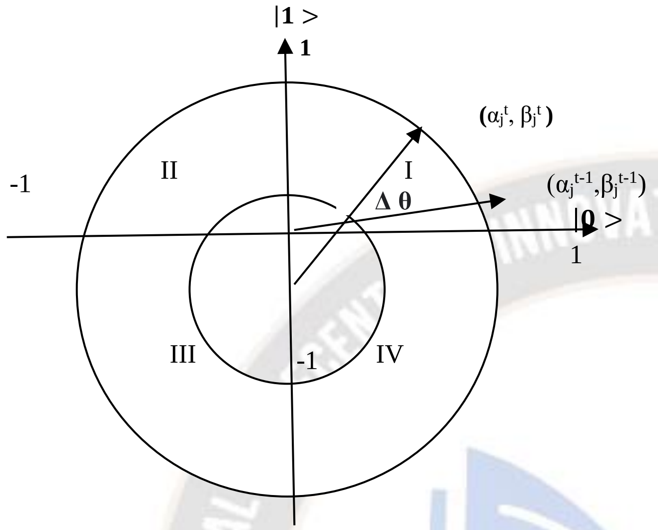

Figure. 1. Qubit rotation strategy using ELS.

The ELS is applied on the best solution obtained after implementation of the quantum gate rotation strategy in the proposed algorithm. The direction of rotation in the ELS depends on the change in rotation angle Δ θ as shown in figure 1. The table 3 shows that effect of rotation angle on the solution quality during implementation of the ELS. the rotation angle using ELS is decided in two ways. If the qubit lies in the first and third quadrant as shown in figure 1 then the value of Δ θ is set to a positive value (+Δ θ) so that probability of achieving state 1 increases. If the qubit remains in the second and fourth quadrants then the Δ θ is set to a negative value so that the probability of achieving state 1 increases.

The complete operational process of the suggested QIEA with elitist search heuristic (QIEA-ELS) is explained as:

1. Set the generation counter equal to zero (t=0).
2. Initialize the qubit individuals (Q (t)): $Q(t) = [q^t_1, q^t_2, q^t_3 \ldots\ldots q^t_n]$, where n is the number of qubit individuals.
3. Observe and find the X(t) from Q(t); (where Q(t) is a group of qubit individuals.)
4. Repair X(t) to meet constraints in eq. (4) to (7) [48-49]
5. Perform fitness evaluation for the X(t). [48-49]
6. Store the best-observed solution in B(t) matrix.
7. Make increment and set t = t+1.
8. Update Q(t) using Rotation Gate and the Best Individual as Attractor
9. Perform an update of the best Individual using the elitist local search method.
10. Find X(t) by observation Q(t-1).
11. Evaluate X(t).
12. Store the observed and updated solution of X(t) in B(t) matrix.
13. Stop if termination criteria meet else repeat steps 6 to step10.

IV. APPLICATION OF PROPOSED ALGORITHM ON VARIOUS TEST SYSTEMS

The proposed algorithm is evaluated on the various unit system consisting of 10 to 100 units. The data of 10 unit is duplicated to use the data in 20,40, 60, 80, 100-unit test systems. Spinning reserves are kept at 10 % of the total load demand. The test cases are evaluated by carrying out 30 trial runs. The suggested QIEA algorithm is applied to the different test cases to evaluate the effectiveness of the algorithm as given below:

- Unit System 1 (US1): 10 thermal generating units.
- Unit System 2 (US2): 20 thermal generating units
- Unit System 3 (US3): 40 thermal generating units
- Unit System 4 (US2): 60 thermal generating units
- Unit System 5 (US2): 80 thermal generating units
- Unit System 6 (US2): 100 thermal generating units

The consumer load demand for 24 hours is given in Table 1. The input data of 10 thermal generators along with constraint parameters are provided in Table 2.

Table 1. Load demand data for 24 hours

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

Table 2. The input data for the 10-unit system

	TU1	TU 2	TU 3	TU 4	TU 5	TU 6	TU 7	TU7	TU 9	TU10
PG_j^{MAX}	455	455	130	130	162	80	85	55	55	55
PG_j^{MIN}	150	150	20	20	25	20	25	10	10	10

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X_j (\$/h)	1000	970	700	680	450	370	480	660	665	670
Y_j (\$/MWh)	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
Z_j (\$/MW2-h)	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
Min_J^{UPTIME} (h)	8	8	5	5	6	3	3	1	1	1
$Min_J^{DOWNTIME}$ (h)	8	8	5	5	6	3	3	1	1	1
$SU_j^{\cos t}$ (\$)	4500	5000	550	560	900	170	260	30	30	30
$SD_j^{\cos t}$ (\$)	9000	10000	1100	1120	1800	340	520	60	60	60
C_J^t (h)	5	5	4	4	4	2	2	0	0	0
G_j^t (h)	8	8	-5	-5	-6	-3	-3	-1	-1	-1

The proposed QIEA with elitist search heuristic (QIEA-ELS) is applied to the unit commitment problem. The elitist search method is a local search method that is used to improve the quality of the best solution in genotype space. The qubits associated with the best individual are rotated in the same direction as determined by the phenotype solution so as to improve their probability to collapse in the current state 0 or 1The parametric testing to determine the best angle of rotation for ELS is performed six different rotation angles viz., 0, 0.002π, 0.02π, 0.025π, 0.03π and 0.015π. However, the remaining parameters were taken to be same as recommended in [29].

The population sizes have been taken of 4 & 18 from [29] based on their parametric study and similarly the rotation angle is taken 0.02π. The best results are found on the rotation angle 0.02π. When the population size used is small, then it provides improved results in less computational time. The larger population size from 18 may provide improved results, but computational time will increase with population size. Infect the selection of population is problem driven issue. The current work is carried out with 50 generations, 30 trial runs with population size of 4 and 18. As the unit commitment problem requires a good solution with in a small duration of time. The QIEA-ELS with population size 4 is able to provide the improved results in lesser computation time. The QIEA-ELS with population size of 18 is also able to improve the results but time duration is higher.

The results of the parametric testing of QIEA-ELS are mentioned in Table 3, which justifies the design and selection of parameters for ELS. The convergence curve for the 10-unit test system at various angles is shown in figure 2. the results are compared with the [29] without using the ELS. It is observed that the result using ELS are found improved in all cases (best, mean, worst). The ELS is applied on the best obtained results to improve them. The normal QIEA-UC [29] uses general gate rotation strategy to improve the solution individuals by moving them in the direction of best solution in every generation. The present work applies also this process and obtained best results and then apply the ELS on obtained best results to improve more the quality of the results. So, it is one more advanced step and ELS provides the better results as compare to the method discussed in the [29]. the ELS with 0.025π is giving better results as compared to all other configurations so we have selected it for further testing given in the next section.

Table3: The effect of the angle of rotation in ELS

Pop. Size	Maximum Gen.	Angle * **π** radian	Best Cost	Mean Cost	Worst Cost	SD
				Cost		
4	50	0	5617583.58	5622223.97	5627217.72	2248.00
4	50	0.002	5616142.97	5622380.08	5628626.23	2797.08
4	50	0.02	5609558.35	5611504.34	5614007.77	1010.85
4	50	0.025	5609099.86	5611387.96	5613833.01	820.18
4	50	0.03	5609534.19	5611415.56	5628626.23	1579.61
4	50	0.015	5610581.45	5612093.63	5614995.20	1133.71

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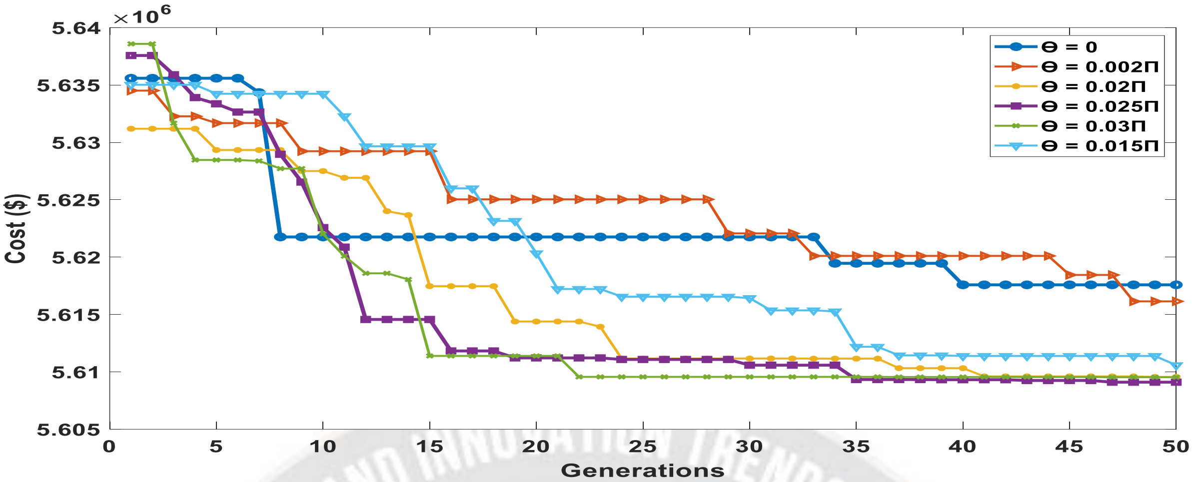

Figure 2. Effect of the angle on the improvement of the results.

V. RESULTS

The proposed QIEA-ELS solved the UCP considering two population sizes and two maximum generation numbers (50 and 100). The result obtained after applying the QIEA-ELS on different unit test systems is provided in table 4 and table 5. the pop size, maximum generation, computational mean time, cost (Best, Mean, and Worst), standard deviation etc. for the QIEA-ELS is provided in the table 4 and 5.

The Average Cost Convergence Curves of the different test systems are shown in figure 3 to figure 8. The results are compared with other well-known solution methods provided in table 6 to table 11. The results are obtained considering two population sizes of 4 and 18 with a maximum generation number of 50. Table 6 shows the comparison of the result for the 10-unit test system with other well-known solution techniques. The results prove the usefulness of the algorithm in achieving the best possible result and reduced computational time with small population sizes. Similarly, table 7 shows the results for the 20-unit test system, table 8 shows the results for 40-unit test system, table 9 shows the results for the 60-unit test system, table 10 and table 11 show the results for the 80 units test system, and 100-unit test system respectively. The results support the claim of reducing cost and computational time with a small population size. Figure 3 to figure 8 show the comparison of both population cases (4 and 18) with cost and generation convergence curves. The convergence curves show that after a certain number of generations and iterations the curves becomes almost constant.

The convergence curves prove the performance of the suggested QIEA-ELS in finding the best solution with less computational time and generation. If we compare the results of the [29] with obtained results of the current work, it is found that the suggested ELS approach can find much improved results. The quality of the solution is increased and the search time is improved.

Table 4. Results of The Suggested Method (QIEA-ELS) with Generation Number Up To 50.

				Cost				
	Pop. Size	Max. Gen	Mean-time	Best	Mean	Worst	S.D	Gen-Max
10	4	50	4.41	563938	563938	563938	0	26
	18	50	19.20	563938	563938	563938	0	14
20	4	50	7.54	1124284	1124716	1124791	126	47
	18	50	33.44	1124243	1124693	1124753	157	50
40	4	50	13.12	2245685	2246749	2247756	549	50
	18	50	58.87	2244116	2246127	2247179	642	50
60	4	50	19.46	3365864	3367231	3367776	451	50
	18	50	86.05	3365102	3366676	3367227	757	50
80	4	50	26.82	4487949	4490642	4493200	1074	50
	18	50	112.77	4488818	4490082	4490804	628	50
100	4	50	41.67	5609100	5611388	5613833	820	50
	18	50	153.34	5607711	5610399	5610968	764	50

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Table 5. Results of The Suggested Methods (QIEA-ELS) with Generation Number Up To 100.

				Cost			
	Pop. Size	Max. Gen	Mean-time	Best	Mean	Worst	S.D
10	4	100	2.18	563938	564289	564714	294
	18	100	9.62	563938	563994	564672	137
20	4	100	3.05	1124244	1125777	1126672	551
	18	100	13.71	1123933	1125048	1125926	439
40	4	100	4.42	2247036	2248207	2249702	801
	18	100	19.83	2246381	2247154	2249242	560
60	4	100	5.82	3369351	3371039	3373062	917
	18	100	26.23	3367186	3369203	3370699	883
80	4	100	7.3	4491896	4494710	4497278	1621
	18	100	32.78	4490537	4491903	4494269	895
100	4	100	8.75	5615242	5618308	5622678	1776
	18	100	39.24	5611696	5614434	5616478	1203

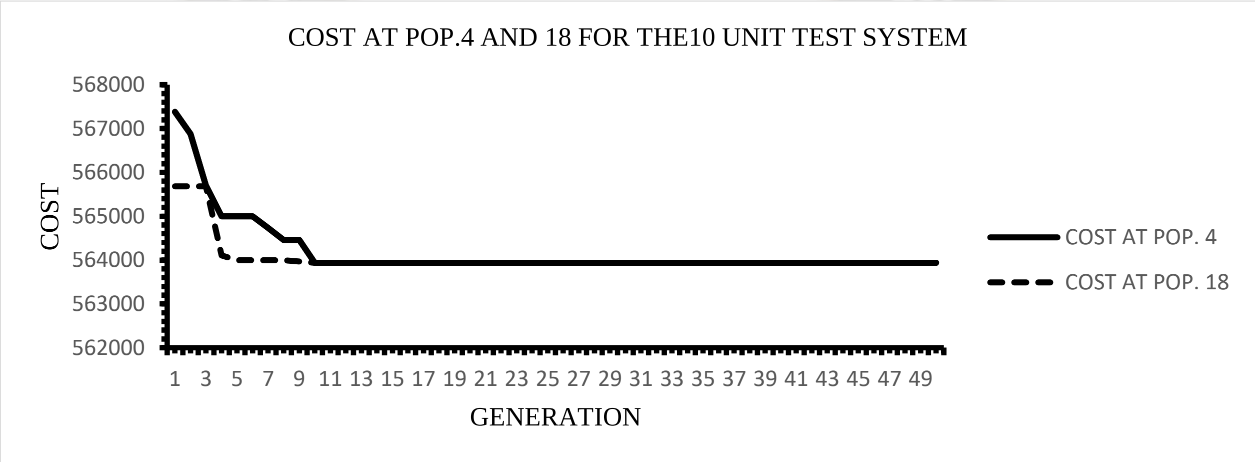

Figure 3. Average Cost Convergence Curves For 10 Unit Test System.

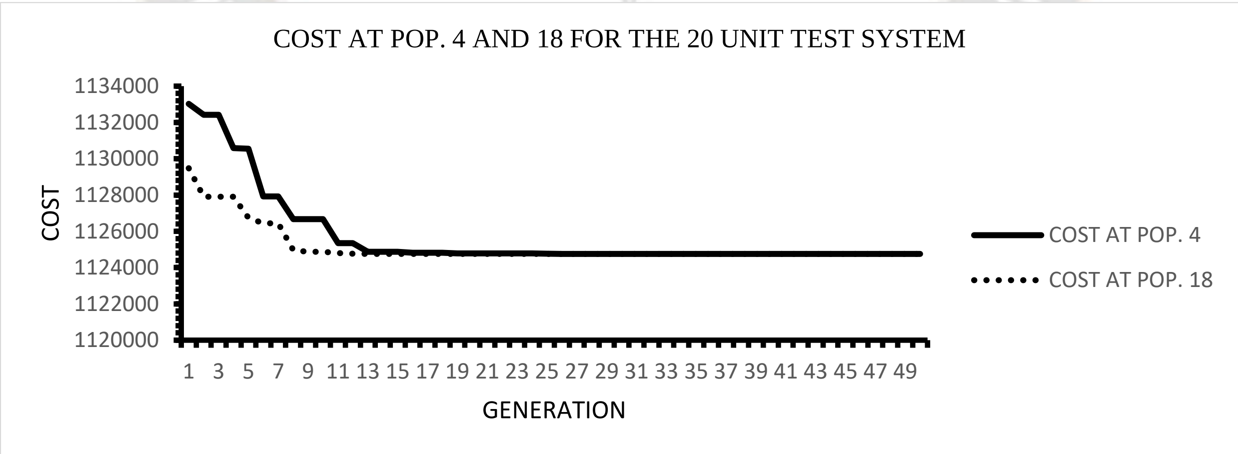

Figure 4. Average Cost Convergence Curves For 20 Unit Test System.

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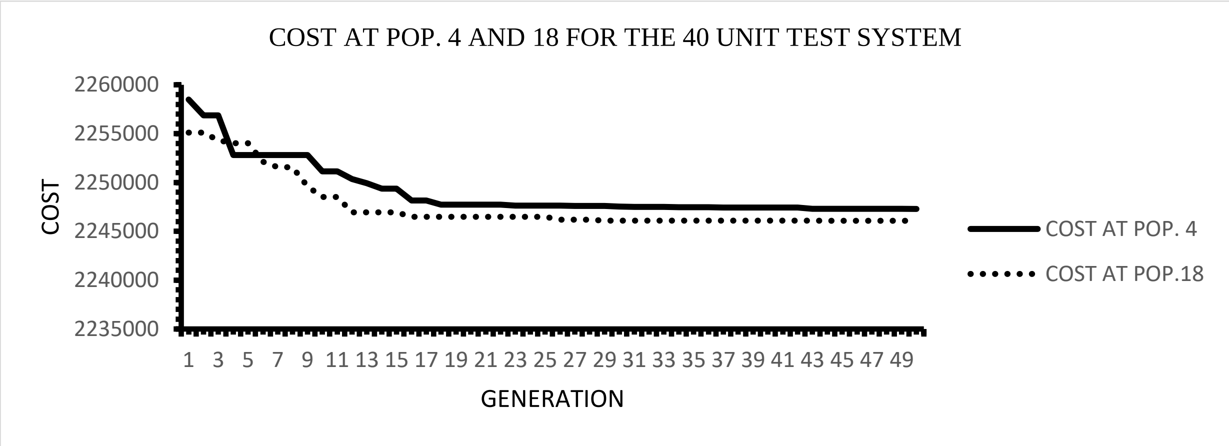

Figure 5. Average Cost Convergence Curves For 40 Unit Test System.

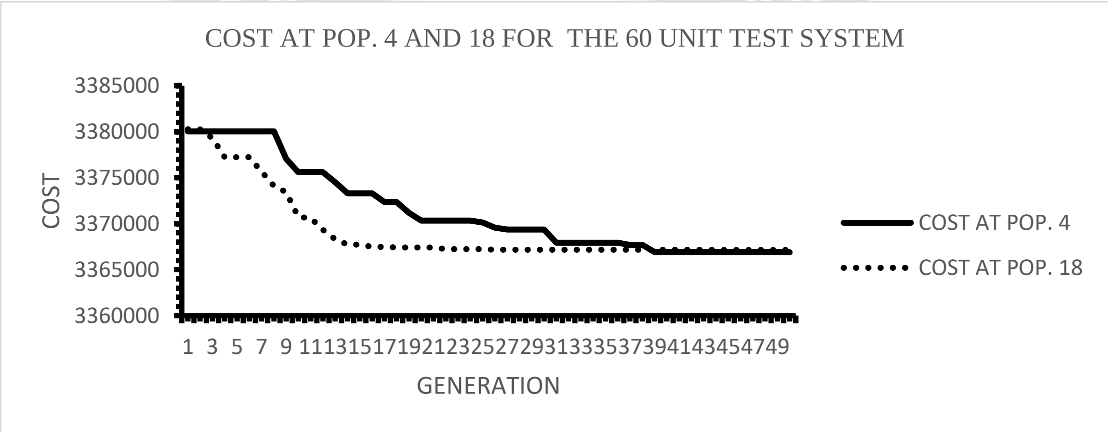

Figure 6: Average Cost Convergence Curves For 60 Unit Test System.

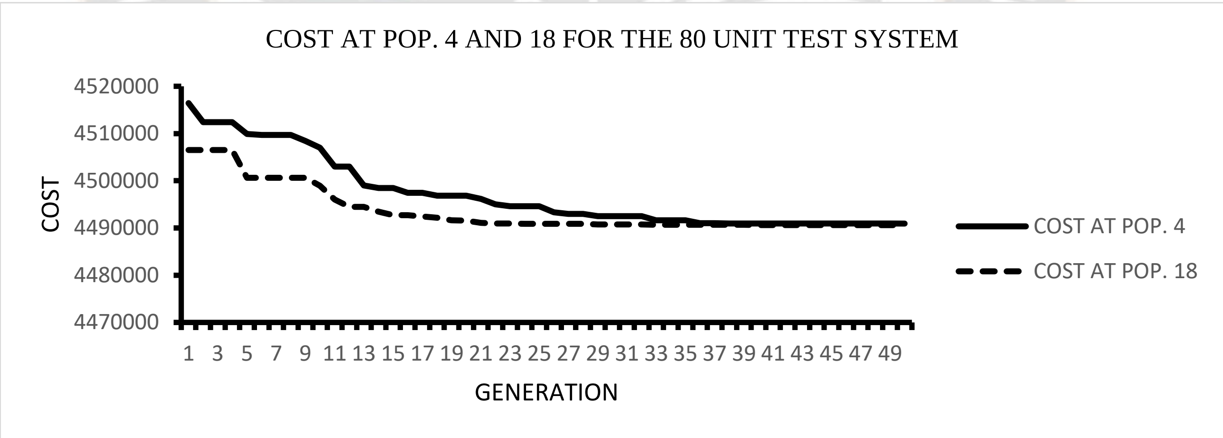

Fig. 7: Average Cost Convergence Curves For 80 Unit Test System.

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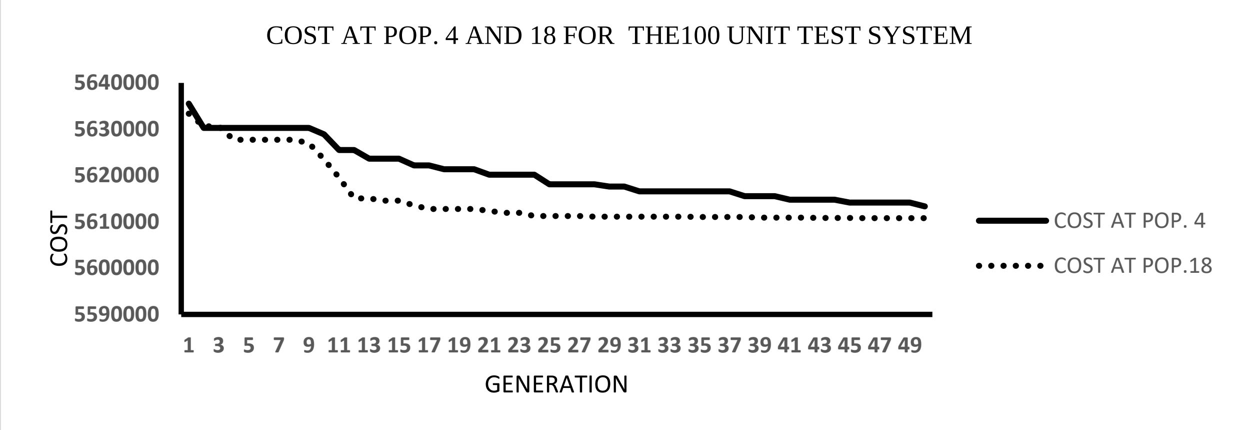

Fig. 8: Average Cost Convergence Curves For 100 Unit Test System.

Table 6: Results Comparison of the QIEA-ELS with other well-known methods for Unit System 1 (US1).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($) Best	Cost ($) Mean	Cost ($) Worst	Mean Time
Unit System 1 (US1)	LR [29]	-	-	-	566107	-	-	257
	GA [29]	20	50	500	565825	-	570032	221
	EP [29]	20	50	500	564551	565352	566231	100
	HPSO [29]	50	20	1000	563942	564772	565785	-
	SA [29]	10	-	-	565828	565988	566260	3
	UCC-GA [29]	20	20	500	563977	-	565606	85
	QEA-UC [29]	30	4	100	563938	564289	564714	2
			18	200	563938	563969	564672	19
	QIEA-ELS	30	4	50	563938	563938	563938	4.41
			18	50	563938	563938	563938	19.20

The results obtained ate compared with other state of art techniques like LR [29] GA [29] HPSO [29] UCC-GA [29] EP [29] QEA-UC [29]. The results provide the information of the parameters used by current work as well as by the other techniques. The results obtained after testing the QIEA-ELS on various test case are given table 6 to table 11.

Table 7. Results Comparison of the QIEA-ELS with other well-known methods for Unit System 2 (US2).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($) Best	Cost ($) Mean	Cost ($) Worst	Mean Time
Unit System 2 (US1)	LR [29]	-	-	-	1128362	-	-	514
	GA [29]	20	50	1000	1126243	-	1132059	733
	EP [29]	20	50	1000	1125494	1127257	1129793	340
	SA [29]	10	-	-	1126251	1127955	1129112	17
	UCC-GA [29]	20	20	1000	1125516	-	1128790	225
	QEA-UC [29]	30	4	100	1124244	1125777	1126672	3
			18	200	1123607	1124689	1125715	28
	QIEA-ELS	30	4	50	1124284	1124716	1124791	7.54
			18	50	1124243	1124693	1124753	33.44

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Table 8. Results Comparison of the QIEA-ELS with other well-known methods for Unit System 3 (US3).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($)			Mean Time
					Best	Mean	Worst	
Unit System 3 (US3)	LR [29]	-	-	-	2250223	-	-	1066
	GA [29]	20	50	2000	2251911	-	2259706	2697
	EP [29]	20	50	2000	2249093	2252612	2256085	1176
	SA [29]	10	-	-	2250063	2252125	2254539	88
	UCC-GA [29]	20	20	2000	2247036	-	2256824	614
	QEA-UC [29]	30	4	100	2247036	2248207	2249702	4
			18	200	2245557	2246728	2248296	43
	QIEA-ELS	30	4	50	2245685	2246749	2247756	13.12
			18	50	2244116	2246127	2247179	58.87

Table 9. Results Comparison of the QIEA-ELS with other well-known methods for Unit System 4 (US4).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($)			Mean Time
					Best	Mean	Worst	
Unit System 4 (US4)	LR [29]	-	-	-	3374994	-	-	1594
	GA [29]	20	50	3000	3376625	-	3384252	5840
	EP [29]	20	50	3000	3371611	3376255	3381012	2267
	SA [29]	10	-	-	-	-	-	
	UCC-GA [29]	20	20	3000	3375065	-	3382886	1085
	QEA-UC [29]	30	4	100	3369351	3371039	3373062	6
			18	200	3366676	3368220	3372007	54
	QIEA-ELS	30	4	50	3365864	3367231	3367776	19.46
			18	50	3365102	3366676	3367227	86.05

Table 10. Results Comparison of the QIEA-ELS with other well-known methods for Unit System 5 (US5).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($)			Mean Time
					Best	Mean	Worst	
Unit System 5 (US5)	LR [29]	-	-	-	4496729	-	-	2122
	GA [29]	20	50	4000	4504933	-	4510129	10036
	EP [29]	20	50	4000	4498479	4505536	4512739	3584
	SA [29]	10	-	-	4498076	4501156	4503987	405
	UCC-GA [29]	20	20	4000	4505614	-	4527847	1975
	QEA-UC [29]	30	4	100	4491896	4494710	4497278	7
			18	200	4488470	4490128	4492839	66
	QIEA-ELS	30	4	50	4487949	4490642	4493200	26.82
			18	50	4488818	4490082	4490804	112.77

Table 11: Results Comparison of the QIEA-ELS with other well-known methods for Unit System 6 (US6).

Test System	Methods	Trials	Pop. Size	MAX. Gen	Cost ($)			Mean Time
					Best	Mean	Worst	
Unit System 6 (US6)	LR [29]	-	-	-	5620305	-	-	2978
	GA [29]	20	50	5000	5627437	-	5637914	15733
	EP [29]	20	50	5000	5623885	5633800	5639148	6120
	SA [29]	10	-	-	5617876	5624301	5628506	696
	UCC-GA [29]	20	20	5000	5626514	-	5646529	3547

	QEA-UC [29]	30	4	100	5615242	5618308	5622678	9
			18	200	5609550	5611797	5613220	80
	QIEA-ELS	30	4	50	5609100	5611388	5613833	41.67
			18	50	5607711	5610399	5610968	153.34

VI. CONCLUSION

The problem of the scheduling of generating units is solved successfully with the fulfillment of constraints and consumer load demand. The effectiveness of the suggested algorithm is tested on the different test systems considering 10 to 100 units The results obtained after implementing the suggested QIEA-ELS algorithm for the solution of the unit commitment problem are found impressive as compared to other state of art solution techniques. The combination of the QIEA and ELS can provide enhanced result quality with reduced time of computation with a small population size. The suggested work is carried out considering two population sizes 4 and 18. The results prove the suggested method can provide enhanced results with a small size population and in a small duration of time. The elitist search method improves the quality of the solution. The suggested approach can be extended further to other problem cases of unit commitment considering various objectives and constraints. The integration of renewable sources with thermal generating units may be considered to solve using the proposed QIEA-ELS.

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