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Adaptive Quantum-Inspired Evolutionary Algorithm for Optimizing Power Losses by Dynamic Load Allocation on Distributed Generators

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Abstract: In this paper, an Adaptive Quantum-inspired Evolutionary Algorithm (AQiEA) has been applied for minimizing the power losses in the distribution network by suitable placement, sizing and subsequent allocation of load on Distributed Generators (DG) for a varying load with a time horizon of twenty-four hours. Many efforts have been reported in the literature to minimize power losses. However, they have mostly used a fixed load, i.e., nonvarying load, whereas it is well known that load in distribution network varies during the day. An investigation was undertaken to find the reduction in power losses on a time-varying load. It has been found that the average power losses for dynamic load allocation on DGs for every hour have a maximum reduction in power loss as compared with other well-known cases in the literature. Optimal location and size of DG is a difficult nonlinear, non-differentiable combinatorial optimization problem. AQiEA is used to find the appropriate location and capacity of DG for a varying load with a time horizon of twenty-four hours to minimize the power losses. AQiEA doesn't require additional operators like local search and mutation to improve the convergence rate and avoid the premature convergence. A Quantum Rotation inspired Adaptive Crossover operator is used as a variation operator, which is parameter free. The effectiveness of AQiEA is demonstrated on two test bus systems viz., 33 bus system and 69 bus system, which are used as benchmark problems for validating the proposed methodology as well as for comparative testing amongst existing techniques. Wilcoxon signed rank test is also used to demonstrate the effectiveness of AQiEA. The experimental results show that AQiEA has better performance as compared to some existing 'state of art' techniques.

Keywords: Distributed Generators; Twenty-four-hour load; Power losses; Dynamic load allocation; Entanglement & Measurement Operator; IEEE 33& 69 bus system.

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Nomenclature:

I_m	magnitude of current at the m^{th} bus
R_m	magnitude of resistance at the m^{th} bus
K	total time-period in a day
$V_m^{\min}$ and $V_m^{\max}$	minimum and maximum acceptable voltage at the m^{th} bus
X_m	magnitude of reactance at the m^{th} bus
Q_{m+1}	reactive load in the system at m+1 bus
P_{loss}	total active power loss in the system
$P_{DG,m}$	active power injected by DG at the m^{th} bus
$P_{DG,m}^{\min}$ and $P_{DG,m}^{\max}$	minimum and maximum allowable limit for active power injection at the m^{th} bus
P_{m+1}	real load in the system at m+1 bus
N_b N_{br}	total number of buses and total number of branches in the system
$P_{Substation}$	total substation power
P_{demand}	total power demand in the system
$V_{m,k}$	voltage at the m^{th} bus on k^{th} time-period
$P_{m+1,k}$	real load in the system at m+1 bus on k^{th} time-period
$Q_{m+1,k}$	reactive load in the system at m+1 bus on k^{th} time-period
$P_{DG,m,k}$	active power injected by DG at the m^{th} bus on k^{th} time-period
$R_{m,k}$	magnitude of resistance at the m^{th} bus on k^{th} time-period
$X_{m,k}$	magnitude of reactance at the m^{th} bus on k^{th} time-period
$P_{Substation,k}$	total substation power at k^{th} time-period
$P_{demand,k}$	total power demand in the system at k^{th} time-period
$P_{loss,k}$	total active power loss on the system at k^{th} time-period

1 Introduction

Evolutionary Algorithms (EA) are principally population-based stochastic searches and optimization techniques, which work on nature's law of evolution and applied for different engineering optimization problems. The population of solutions is evolved in EA by using operators like selection, crossover, mutation, and local heuristics to find near-optimal solutions. Selection operator generally gives direction to evolution based on the Darwinian principle. The solution for the next iteration is generated through a crossover operator by recombining the solutions from the current iteration. Local heuristics and mutation operator are used to improve the exploration and exploitation, i.e., escaping from local minima and increasing the convergence rate. EAs are popular due to their ease of implementation and employed for solving difficult and complex optimization problems. However, EA often suffers from limitations like stagnation, sensitive to the choice of operator parameters, premature convergence, and slow convergence. Quantum-inspired Evolutionary Algorithm (QiEA) is used to overcome the limitations. QiEA uses probabilistic representation with some concepts and operation of quantum computing [1]. QiEA uses a single *Q*-bit with small population size and is governed by the principle of quantum mechanics [2]. *Q*-gates are used in QiEA as a variation operator to drive the individuals in the population towards better solutions. In recent times, Adaptive Quantum-inspired Evolutionary Algorithm (AQiEA) [3] is applied on various engineering optimization problems with a measurement operator. AQiEA uses two *Q*-bits, whereas QiEA uses a single *Q*-bit per decision variable in a solution vector. Moreover, AQiEA doesn't require any other operators like mutations or local heuristics to drive the individuals toward convergence. Recently, AQiEA is applied to some engineering optimization problems like ceramic grinding [4], optimal location and size of Distributed Generators (DG) [5], Network Reconfiguration [6], Siting and sizing of Capacitors [7], Cost analysis of DG & Capacitor [8] and simultaneous implementation of both DGs and capacitors [9], and has shown better performances as compared with other approaches.

DG is defined as the small scale power generating source which is placed nearer to the load centers, and its size varies from few KW to several MWs [10]. Since DGs are placed nearer to load centers, power transmission cost and the overall power losses produced in the distribution system are reduced. Placement and sizing of DG are two major factors which are playing a key role to minimize the power losses, however optimal location and capacity of DG not only reduces the power losses but also improves the overall voltage profile in the system. If the optimal allocation of DG is inappropriate, overall power losses produced in the distribution system are increased to a maximum value higher than the losses without DG. Optimal location and capacity of DG in a distribution system is a difficult combinatorial optimization problem and has attracted the interest of many researchers. Different analytical methods [11−13] and metaheuristics algorithms [14−26] are applied to solve this combinatorial optimization problem with an objective to reduce power losses. Different types of DGs which inject active and reactive powers based on terminal characteristics, different types of load models based on voltage-dependent characteristics are considered in the literature.

C. Wang and M. H. Nehrir [11], T. Gozel and M. H. Hocaoglu [12] and M. M. Aman *et al.* [13] used different analytical approaches for optimal allocation of DG to reduce the losses. C. Wang and M. H. Nehrir [11] used time variant and time invariant loads with unity power factor DG on radial and networked systems. T. Gozel and M. H. Hocaoglu [12] used the equivalent current injection technique based on topological characteristics of a distribution network. M. M. Aman *et al.* [13] used a power stability index to identify the most critical bus, which causes voltage instability in the system. Effectiveness of proposed analytical approaches is tested on the 6 bus system and 30 bus system by C. Wang [11], whereas T. Gozel and M. H. Hocaoglu [12] and M. M. Aman *et al.* [13] used the 12 bus and 69 bus system. The main drawback for the above mentioned analytical approaches are DG size is not considered [11], applied only on small bus systems [12] and single DG is used for optimal allocation of DG [13].

Metaheuristics methods are population-based optimization techniques with high computational robustness. In most of the works, to minimize the power losses in the distribution system with DG integration, population-based metaheuristics are used as solution strategies. Chaotic Symbiotic Organism Search (CSOS) [14], Symbiotic Organism Search (SOS) [15], Combined Genetic algorithm (GA)/ Particle Swarm Optimization (PSO) [16], Grey Wolf Optimization (GWO) [17], Stochastic Fractal Search (SFS) [18], Quasi-oppositional Teaching Learning Based optimization method (QOTLBO) [19], Krill Herd Algorithm (KHA) [20], Two Adaptive GA [21], Grid-based Multi-objective Harmony Search Algorithm [22], Multi-Objective Evolutionary algorithm based on decomposition (MOEA/D) [23], Harmony Search Algorithm (HSA) [24], Fire Work Algorithm (FWA) [25], Adaptive Cuckoo Search Algorithm (ACSA) [26] and Gravitational Search Algorithm (GSA) [27] are some of the well-known optimization techniques used to reduce the power losses.

S. Saha and V. Mukherjee [14], B. Das *et al.* [15], M. H. Moradi and M. Abedini [16] and U. Sultana *et al.* [17] used different metaheuristics for optimal placement and sizing of DG with an objective to minimize the power losses and improve the voltage stability of the network. S. Saha and V. Mukherjee [14] and B. Das *et al.* [15] also tested the effectiveness of their proposed algorithms with some numerical engineering optimization problems. U. Sultana *et al.* [17] used a multi-objective function with weighted sum to minimize the reactive power losses. However, in addition to the objectives mentioned above, voltage profile improvement is also included by T. P. Nguyen and D. N. Vo [18]. S. Saha and V. Mukherjee [14], B. Das *et al.* [15] and M. H. Moradi and M. Abedini [16] tested the effectiveness of their proposed algorithms with the 33 bus system and 69 bus system. T. P. Nguyen and D. N. Vo [18] also tested the effectiveness with same bus systems, but also, he added one more bus system, i.e., 118 bus system. S. Sultana and P. K. Roy [19, 20] used two different metaheuristic algorithms for optimal location and capacity of DG with an objective to reduce the power losses and improve the voltage profile. The effectiveness of the proposed metaheuristics is tested on small, medium and large scale bus systems in comparison with stochastic search algorithms like loss sensitivity factor simulated annealing (LSFSA), GA and Combined GA and PSO.

S. Ganguly and D. Samajpati [21] used different types of DGs (supplying reactive power, operating at UPF (Unity Power Factor) and consuming Reactive power) with on-load tap changer (OLTC) to maximize the bus voltage deviation and reduce the network losses. Indian practical distribution network (52 bus system) and 69 bus system are used to demonstrate the results. S. Kayalvizhi and D. M. V. Kumar [22] also used different DGs, i.e., dispatchable and non-dispatchable with the same objective as above and tested on the 33 bus system, 69 bus system, and 85 bus system. P. P. Biswas *et al.* [23] operated DG in parallel with shunt capacitors to minimize both active and reactive power losses with the same bus system as above. Some researchers [24−26] have integrated both strategic allocations of DG along with network reconfiguration in the distribution system to maximize the percentage power loss reduction and improve voltage profile. Sumit Banerjee *et al.* [28] used a voltage stability index method with a different load model to improve the voltage profile in the distribution network, this method determines the most sensitive buses which are nearer to voltage collapse. Manikanta *et al.* [29] also studied the effect of DG with same load model to maximize the percentage power loss reduction in the distribution system.

Kumar *et al.* [30] proposed a new algorithm EBOwithCMAR, which is the winner of CEC-2017 benchmark problems. This method combines the characteristics of local optimizer and global optimizer. In EBOwithCMAR, two algorithms EBO and CMAR are applied to a particular iteration with respect to their probabilities. Success History Based Adaption (SHBA) and Linear Population Size Reduction (LPSR) are used to resize the population and uses a retreat phase viz., Covariance Matrix Adapted Retreat Phase (CMAR), which improves the search capability of EBO. Whereas, AQiEA is a probabilistic EA and population-based approach inspired by integrating some principles of quantum mechanics. It is a relatively new and powerful evolutionary intelligence method used for solving many engineering optimization problems. AQiEA uses two quantum-bits (Q-bits), where quantum-bits are analogous to classical bits. In AQiEA, two Q-bits are entangled with one another and represented on a classical system as though they exist in a quantum system with respect to the superposition of basis state, which increases the population diversity. Three rotation strategies are used to converge the population adaptively towards global optima.

All of the efforts, as mentioned earlier, have used distribution systems with a fixed load, whereas it is well known that load in a distribution network varies during the day. An investigation was undertaken to find the reduction in losses on a time-varying load with a time horizon of twenty-four hours. Therefore, a novel methodology is formulated to reduce the power losses with five different scenarios on time horizon of twenty-four hours instead of a single hour.

The main contribution of the paper is as follows.

– AQiEA is used to solve the placement and sizing of DG viz., a difficult combinatorial optimization problem.
– A novel methodology is described for placement and sizing of DG for a varying load with a time horizon of twenty-four hours instead of one hour.
– The proposed algorithm is implemented with different scenarios to minimize the power losses for the 24-hour load profile.

Rest of the paper is organized as follows. Section II describes AQiEA, which is used to solve the combinatorial optimization problem. Section III defines the problem formulation on time horizon of twenty-four hours instead of a single hour. The methodology proposed to reduce the power losses for varying load with a time horizon of twenty-four hours with optimal placement and sizing of DG is explained in Section IV, Section V demonstrates the results with AQiEA on benchmark test bus systems to minimize the power losses. Section VI concludes the paper.

2 Algorithm

Quantum-inspired evolutionary algorithms:

QiEA is a population-based probabilistic EA, which is designed by adopting some concepts and principles of quantum computing such as quantum-inspired bits (*Q*-bits), quantum gates (*Q*-gates), interference, superposition, entanglement, and measurement. It is used to overcome the limitations associated with EA and applied on various engineering optimization problem. *Q*-gates are used in QiEA as a variation operator to drive the individuals in the population towards better solutions. QiEA uses probabilistic representation with *Q*-bit. *Q*-bit representation has a better characteristic of population diversity than other representations. *Q*-bit is defined as the smallest unit of information in a quantum computer. A *Q*-bit may be represented in state '*a*', in state '*b*' or superposition of two states, where state '*a*' and state '*b*' are two basis states of a two-dimensional quantum system. The state of the *Q*-bit can be represented as

$$|\alpha\rangle = X_1|a\rangle + X_2|b\rangle, \tag{1}$$

where X_1 and X_2 are probability amplitudes associated with corresponding states. $|X_1|^2$ and $|X_2|^2$ gives the probability of *Q*-bits to be found in state '*a*' or '*b*' respectively. A *Q*-bit individual '*q*' with m-bits is given as follows

$$q\begin{bmatrix} q_1 & q_2 & \cdots & q_m \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & X_{2m} \end{bmatrix}, \tag{2}$$

where $|X_{1i}|^2 + |X_{2i}|^2 = 1, \ \ i = 1,2,...,m.$

These are evolved by unitary transformation and constrained with several limitations in a quantum system. On classical computers, these *Q*-bits produce inefficient simulations. In QiEA, *Q*-bit probabilistic nature is widely used for maintaining diversity. Quantum gate operators are used to evolve the solution vectors which are influenced by phase rotation transformation.

Proposed Algorithm:

AQiEA is used to find optimal placement and sizing of DG for a varying load on time horizon of twenty-four hours, which is a difficult nonlinear, non-differentiable combinatorial optimization problem. Each solution vector has two *Q*-bit vectors associated with it, which helps in utilizing the entanglement principle. Entanglement is described as if two or more *Q*-bit vectors, which are entangled with one another, then if any operation is performed on one of the *Q*-bit vectors, it would affect the state of another *Q*-bit vector. It overcomes some of the limitations associated with EA implementation. In EA, the objective function value feedback is not being utilized properly, AQiEA uses two *Q*-bit vectors, first *Q*-bit vector stores the scaled solution vector, and the other is used to store the scaled and ranked objective function value of the solution vector. The information stored in the first and the second *Q*-bit vectors are entangled; the first *Q*-bit vector influences the second *Q*-bit vector as the amplitude of the first *Q*-bit vector determines the objective function value. The second Q-bit vector is used as a feedback parameter in the tuning free adaptive quantum inspired rotation crossover operator for evolving the first *Q*-bit vector.

A measurement operator is used to generate a solution string from the first *Q*-bit vector string (*X*). In quantum computers, a resultant classical state is observed upon application of measurement operator, which results in a collapse of superposition of states. However, in classic computers collapse of states doesn't occur naturally. In order to observe the first *Q*-bit string, a new string with a random number, whose value varies between 0 and 1 is generated (N_r), which is of the same length as that of *Q*-bit strings. Hence after measurement operation on the *Q*-bit string, a new measured value string (Q_m) is generated, which is of the same length as *Q*-bit string. **Table 1** shows the measured operator on *Q*-bit string. The measured value in $\boldsymbol{Q_{mj}}$ is obtained by comparing the generated random number at $\boldsymbol{N_{rj}}$ to the square of $\boldsymbol{X_{1j}}$ at j^{th} generation. If $\boldsymbol{N_{rj}}$ is less than the square of $\boldsymbol{X_{1j}}$, $\boldsymbol{Q_{mj}}$ is set to the square of $\boldsymbol{X_{1j}}$ otherwise to the square of $\boldsymbol{X_{2j}}$.

Table 1
Working of Measurement operator on Q-bit string.

$\boldsymbol{j}$	**1**	**2**	**...........**	$\boldsymbol{N_p}$
$\boldsymbol{X_{1j}^2}$	0.17	0.41	....	0.56
$\boldsymbol{X_{2j}^2}$	0.83	0.59	....	0.44
$\boldsymbol{N_{rj}}$	0.24	0.07	....	0.12
$\boldsymbol{Q_{mj}}$	0.83	0.41	....	0.56

The power losses are minimized by placing and sizing the DG; the solution vector for solving the problem is represented in Fig. 1 as follows:

$$\underbrace{X_1 \quad X_2 \ldots\ldots\ldots\ldots \quad X_{n-1}}_{\text{Location of DG}} \quad \underbrace{Y_1 \quad Y_2 \ldots\ldots\ldots\ldots \quad Y_{n-1}}_{\text{Size of DG}}$$

Fig. 1 – *Solution vector representation for DG with optimal location and sizes.*

X_1 to X_{n-1} represents total number of DGs placed in the system and the optimal candidate bus location for each DG is varied from 2 to N_b and is normalized between 0 to 1 for Q-bit representation. Whereas, Y_1 to Y_{n-1} represents optimal capacity of DG which is varied between the minimum and maximum limits i.e., $P_{DG,m}^{\min}$ and $P_{DG,m}^{\max}$ of DG and is normalized between 0 to1 for Q-bit representation.

The amplitude X_2 is discarded, and it is computed from equation (2) whenever it is needed. Quantum registers are used to store the Q-bit vectors. The total number of Q-bit vectors used per quantum register QR_1 is dependent on the number of variables. The structure of QR_1 is shown below:

$$\begin{aligned} QR_{1,1} &= \left[X_{2_{1,1,1}}, X_{2_{1,1,2}}, \ldots, X_{2_{1,1,n}} \right] \\ QR_{1,30} &= \left[X_{2_{1,30,1}}, X_{2_{1,30,2}}, \ldots, X_{2_{1,30,n}} \right]. \end{aligned} \tag{3}$$

The second set of Q-bit vectors is stored in quantum register QR_2 and is used to store the scaled and ranked objective function value of the corresponding solution vector in QR_1. The fittest solution vector and the worst solution vector are assigned one and zero, respectively and is stored in the second Q-bit vector. The remaining solution vectors are also ranked and scaled between the range of zero and one.

The inspiration of Superposition and Entanglement principles is mathematically represented as follows.

$$\left|\alpha_{2i}(\mathrm{t})\right\rangle = f_1\left|\alpha_{1i}(\mathrm{t})\right\rangle , \tag{4}$$

$$\left|\alpha_{1i}(\mathrm{t}+1)\right\rangle = f_2\left(\left|\alpha_{2i}(\mathrm{t})\right\rangle,\left|\alpha_{1i}(\mathrm{t})\right\rangle,\left|\alpha_{2j}(\mathrm{t})\right\rangle\right), \tag{5}$$

where t is iteration number, $\left|\alpha_{1i}\right\rangle$ and $\left|\alpha_{1j}\right\rangle$ are i^{th} and j^{th} solution vectors which are associated with first Q-bit vectors, f_1 and f_2 are two functions through which both the Q-bits are classically entangled, $\left|\alpha_{2i}\right\rangle$ is i^{th} solution vector associated with the second Q-bit vector. Quantum gate operators are used to evolve the solution vectors which are influenced by phase rotation transformation. A quantum rotation inspired adaptive, and parameter tuning free crossover operator is designed for the proposed algorithm. By using the second Q-bit vector's amplitude, the degree of rotation for evolving the first Q-bit vector is determined. For this purpose, the following equation is used:

$$\left|\alpha_{1i}(\mathrm{t}+1)\right\rangle = \left|\alpha_{1i}(\mathrm{t})\right\rangle + f\left(\left|\alpha_{2i}(\mathrm{t})\right\rangle,\left|\alpha_{2j}(\mathrm{t})\right\rangle\right)\left(\left|\alpha_{1j}(\mathrm{t})\right\rangle - \left|\alpha_{1i}(\mathrm{t})\right\rangle\right), \tag{6}$$

where $\left|\alpha_{1j}(\mathrm{t})\right\rangle$ and $\left|\alpha_{1i}(\mathrm{t})\right\rangle$ are two solution vectors, which are chosen deterministically or randomly in the adaptive crossover operator. If $\left|\alpha_{1i}(\mathrm{t})\right\rangle$ has a lesser rank than $\left|\alpha_{1j}(\mathrm{t})\right\rangle$ then $\left|\alpha_{1i}(\mathrm{t})\right\rangle$ is rotated towards $\left|\alpha_{1j}(\mathrm{t})\right\rangle$. If $\left|\alpha_{1i}(\mathrm{t})\right\rangle$ has a better solution than $\left|\alpha_{1j}(\mathrm{t})\right\rangle$ then $\left|\alpha_{1i}(\mathrm{t})\right\rangle$ is rotated away from $\left|\alpha_{1j}(\mathrm{t})\right\rangle$. By using three rotation strategies (R-I, R-II, R-III), variation operator converges the search towards better solutions.

Rotation towards the Best Strategy (R-I):

In this method of rotation, all the first Q-bit vectors are rotated towards the best first Q-bit vector. By rotating all the first Q-bit vectors towards the best first Q-bit vector, it is expected that a better candidate solution will be found for all other solution vectors.

Rotation away from the Worse Strategy (R-II):

In this method of rotation, the best individual in the population will move away from all other individuals. The search takes place in the direction that may result in improving the best individual as it is moving away from the inferior individuals. In the initial part of the search, when most of the individuals are far from each other, it provides for exploration. However, during later part of the search, when other individuals are near the best individual, it provides for exploitation as there are better chances of finding a good candidate solution in the vicinity of the best individual.

Rotation towards the Better Strategy (R-III):

In this method, two individuals are randomly selected, and the individual with the inferior objective function value is rotated towards the individual with the better objective function value as it is expected that inferior individual would improve by moving towards the better individual.

The pseudo code of the proposed algorithm, along with a description, is given as follows:

```
t ← 0
   a. Initialize (QR1 (t))
While (! termination_criteria)
{
   b. Qm = Measurement_operation(QR1 (t))
   c. f(x)= Compute_fitness (Qm(t))
   d. QR2(t)= Rank_Scaled (f(x))
   e. QR1c= AQRC_(QR1(t), (QR2(t))
   f. Tourn_Selection (QR1(t), f(x))
t ← t+1
}
```

Description:

1. Population size, maximum number of iterations, and no of variables are initially assigned for quantum register. *Q*-bits in quantum register QR_1 are initialized with random value between 0 anda 1 drawn from uniform distribution.
2. New string with a random number, whose value varies between 0 and 1 is generated (N_r), which is of the same length as the first *Q*-bit strings. Hence, after measurement operation on the *Q*-bit string, a new measured value string (Q_m) is generated, which is of the same length as the *Q*-bit string.
3. Placement and capacity of DG is a difficult nonlinear, combinatorial optimization problem. In this approach, quantum register Q_m is transferred back to phenol-type space (decision variable space) for computing the fitness of the solution vector. A direct load flow (DLF) [29] is used compute the fitness, which was proposed by J. H. Teng. DLF is formed by two matrices BIBC and BCBV. It is one best known method and has been used in many similar works [5 − 9, 29]. The complete overview of DLF is given in [29].
4. The second *Q*-bit vectors QR_2 stores scaled and ranked for solution vector with value [1, 0]. The fittest first *Q*-bit vector and worst first *Q*-

bit vector in the second Q-bit vector have value 1 and 0, respectively. The remaining solution vectors in the second Q-bit vector are assigned values between 0 and 1.

5. Three rotation strategies (R-I, R-II, R-III) are used for converging the individuals toward better solutions.
6. By applying tournament selection between individuals and their off-springs, the fitter one will move to the next generation.

3 Problem Formulation

In recent times, the deficit of power at load centers is increasing day by day. One of the alternatives to reduce the deficiency of power in the distribution system is by the implementation of DGs into the system. The objective function for a single hour load is considered as follows:

$$\min\{P_{loss}\}=\sum_{m=1}^{N_{br}}\left|I_m\right|^2 R_m . \tag{7}$$

A voltage stability index is considered for computing the bus voltage amplitude against the changes in load demand. The demand at load centers in the distribution network is not fixed, and it varies in a day.

$$VSI_{m+1}=\left|V_m\right|^4-4\left(P_{m+1}X_m-Q_{m+1}R_m\right)^2-4\left(P_{m+1}R_m-Q_{m+1}X_m\right)\left|V_m\right|^2 . \tag{8}$$

The following constraints are considered in distribution system before placing and sizing of DG.

Operation of Distributed Generator:

$$P_{DG,m}^{\min}\le P_{DG,m}\le P_{DG,m}^{\max} . \tag{9}$$

The power injected by DG at m^{th} bus will always be in minimum and maximum acceptable limits.

Power injection for the system:

$$\sum_{m=1}^{n}P_{DG,m}\le P_{demand}+P_{loss} , \qquad n=\text{no. of } DG \tag{10}$$

Overall power generated by all DG units should not exceed the total demand and losses in the system.

Voltage limit:

$$V_m^{\min}\le V_m\le V_m^{\max} . \tag{11}$$

Placing and sizing of DG play an important role in improving the overall efficiency and reliability of the system. The load at the distribution system is not fixed and changes during the day due to its varying nature. In the proposed approach, a new problem is formulated to reduce the power losses in a distribution network, which is based on the time horizon of twenty-four hours in a day, for finding the location and capacity of DG. The objective to reduce the average power loss in the distribution system on time horizon of twenty-four hours is given by:

$$\min\{P_{Avg.\ loss}\} = \frac{1}{24}\left(\sum_{k=1}^{24}\left(\sum_{m=1}^{N_{br}}\left|I_{m,k}\right|^2 R_{m,k}\right)\right). \tag{12}$$

The voltage stability index for 24-hour load is given as follows.

$$VSI_{m+1} = \frac{1}{24}\left(\sum_{m=1}^{N_{br}}\left[\left|V_{m,k}\right|^4 - 4\left(P_{m+1,k}X_{m,k} - Q_{m+1,k}R_{m,k}\right)^2 - \right.\right.$$
$$\left.\left. - 4\left(P_{m+1,k}R_{m,k} - Q_{m+1.k}X_{m,k}\right)\left|V_{m,k}\right|^2\right]\right). \tag{13}$$

The following constraints are considered in the distribution system for the twenty-four-hour load before placing and sizing DG.

Operation of Distributed Generator:

$$P_{DG,m,k}^{\min} \le P_{DG,m,k} \le P_{DG,m,k}^{\max}. \tag{14}$$

The power injected by DG at m^{th} bus on the k^{th} time-period should always be between minimum and maximum acceptable limits.

Power balance for the system:

$$\sum_{m=1}^{n} P_{DG,m,k} + P_{Substation,k} = P_{demand,k} + P_{loss,k}. \tag{15}$$

The total power demand on the system and the overall power losses produced in the system should always be equal to substation power and total power injected by DG on time horizon of twenty-four hours.

Voltage limit:

$$V_{m,k}^{\min} \le V_{m,k} \le V_{m,k}^{\max}. \tag{16}$$

Placement and capacity of DG not only reduces the power losses but also improves the voltage profile in the system. After placing DG on twenty-four-hour load profile, the voltage profile of the system for every hour should always be in permissible limits.

4 Proposed Methodology

Placement and sizing of DGs have been primarily performed to minimize the power losses in the distribution network. Most of the reported efforts have considered a fixed loading condition (Single hour load). However, it is well known that load varies drastically in distribution network during the day as well as with season. This paper has initially investigated the impact of the proposed algorithm on the placement and size of DG with a fixed load. The load profile on distribution system varies drastically during the day; the initial configuration (location and capacity of DGs) is considered the same as for twenty-four-hour load. It is assumed that the average power losses of twenty-four-hour load are high as compared with the fixed load. The power losses for the twenty-four hour load with fixed location and fixed size of DG may be reduced by varying the maximum load allocated on the DG for every hour, i.e., by changing the DG's output, if the DG's output could be varied as per changes in load profile. In this paper, an effort was made to place and size the DG by considering a twenty-four-hour load profile instead of a fixed load. It was assumed that the location and capacity of DG considering twenty-four hour load profile would reduce the losses. Further, it is assumed that by changing the DG's output, losses can be reduced as DG's output could be tuned to the changes in load profile, for a twenty-four hour load profile as compared to the power losses for a configuration with fixed location and fixed size of DGs. The average power losses may be reduced to a minimum value by varying the load allocated on the DG with fixed location and varying the output subject to maximum capacity.

In this paper, a new methodology has been proposed to minimize the power losses in the distribution system on a time horizon of twenty-four hour load by suitably placing, sizing and dynamic allocation of load on DG. It is observed that the number of variables, constraints and load-flow calculations for this problem has increased linearly with the number of hours for different scenarios, so the proposed problem is much more complex as compared to the single fixed hour load placement and sizing problem.

The detailed analysis for minimization of power losses for the twenty-four hour load by placing, sizing, and allocation of load on DG is performed with five different scenarios on two test bus systems:

Scenario I. Single hour load is considered for suitable placement and sizing of DG to minimize the power losses in the distribution system (standard test case from literature).

Scenario II. Average power losses for twenty-four hour load are computed with fixed location and capacity of DG. The location and capacity of DGs are the same as in Scenario I.

Scenario III. Average power losses for twenty-four hour load are computed with fixed location and varying the load allocated on DG to its maximum capacity for every hour, assuming that DG is dispatchable. The location and maximum capacity of DG are the same as in Scenario II.

Scenario IV. The twenty-four hour load has been used for suitable placement and sizing of DG to minimize the average power losses in the distribution system (a novel methodology on twenty-four hour load to minimize the average power loss is proposed, and load data is given in the appendix).

Scenario V. Average power losses for 24-hour load are computed with fixed location and varying the load allocated on DG to its maximum capacity for every hour, assuming that DG is dispatch-able. It is similar to Scenario III, however in this scenario location of DGs is same as in Scenario IV.

5 Testing, Results and Discussion

The effectiveness of AQiEA is tested on two standard IEEE test bus systems. The proposed algorithm is implemented in Matlab 2011b, and exhaustive tests have been carried out on Intel® Core TM i3 CPU 4GB of RAM capacity and @1.80GHz processor. Two cases are considered to analyze the superiority of AQiEA. In the first case, five scenarios are used to minimize the power losses on the time horizon of twenty-four hours. The number of independent runs for each scenario is thirty and based on the performance of these runs at each scenario, average power losses and their standard deviations have been calculated. Wilcoxon signed ranked test [31 – 32] is also used to validate the results statistically. H_0 and H_1 represents the null and alternate hypothesis for each test cases. The performance of AQiEA as compared with the existing 'State of Art' techniques is analyzed in another case. Each technique is analyzed with thirty independent runs, average power loss, and standard deviation are calculated based on the results of the test cases. Wilcoxon's signed rank test is used to perform the pair-wise comparison between two algorithms.

Test bus systems:

The thirty-three bus system consists of thirty-three nodes, thirty-seven branches including both sectionalizing switches and tie line switches. Under normal operating conditions, the minimum and maximum voltages are 0.95p.u and 1.05p.u with voltage rating of $V_{base} = 12.66\,\text{kV}$ and $S_{base} = 100\,\text{MVA}$. From [24] load data and branch data are taken, the total load of the system is 3715 kW and 2300 kVAr. The sixty-nine bus system consists of sixty-nine nodes, seventy-three branches including both sectionalizing switches and tie line switches. From [24] load data and branch data are taken, the total load on the network is 3.801 MW and 2.694 MVAr. Minimum and maximum voltages are 0.95p.u and 1.05p.u with voltage rating of $V_{base} = 12.66\,\text{kV}$ and S_{base}=100 MVA.

Case A

In this case, three DGs are optimally sized and placed to minimize the power losses through the proposed algorithm. The range of allowable size of DG for installation is between 0 to 1 MW for both systems. The superiority of the proposed methodology is analyzed using five scenarios. The parameters of

AQiEA used in the simulation are population size-50 and maximum iterations-200.

33 bus system:

Scenario I is used to find the optimal placement and capacity of DG for minimization of power losses. In Scenario I, real power losses are reduced to minimum value by optimally placing and sizing the DG at locations 25, 14, 30 with DG size 768 kW, 917 kW, and 1 MW respectively, which are shown in **Table 2**. Scenario II is the same as Scenario I, but single hour load data in Scenario I is converted into twenty-four hour load data by mapping as given in the Appendix. The power losses obtained in this case are for twenty-four hours with fixed location and fixed size as Scenario I (i.e., DG at locations 25, 14, 30 with DG size/contribution as 768 kW, 917 kW, and 1 MW respectively for twenty-four hours). Scenario III is same as Scenario II, but in Scenario III the optimal location of DG is fixed, and its load allocation is varied for every hour with the maximum allowable size 768 kW, 917 kW, and 1 MW respectively, assuming that DGs are dispatchable. As a result, the power losses in Scenario III are less as compared to Scenario II. Scenario IV is the same as Scenario I, location and capacity of DG in Scenario I is optimized for a single hour power load, but in the case of Scenario IV, the optimization is performed for twenty-four hours load profile. The power losses obtained in Scenario IV are less than Scenario II but higher than Scenario I. The power losses obtained in Scenario IV are higher than Scenario I as the load in Scenario IV is varying during twenty-four hours but in case of Scenario I, the load remains unchanged during twenty-four hours period. **Table 2** shows Scenario IV is producing lesser power losses by placing and sizing DG at 30, 24, 14 and 1 MW, 1 MW and 788 kW respectively as compared with Scenario III, and Scenario II.

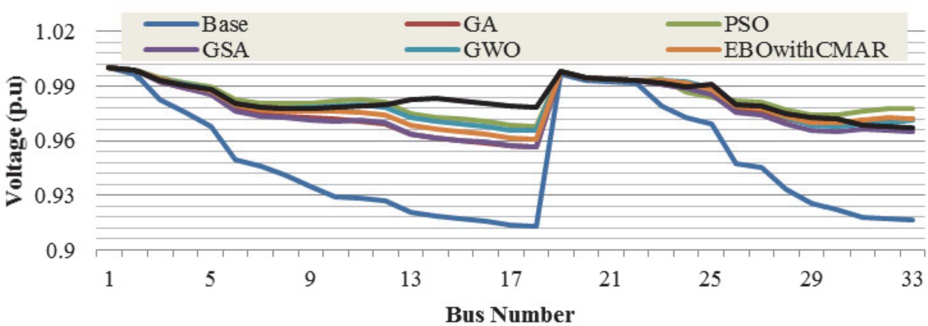

Fig. 2 – *Voltage Profile improvement of 33 bus system for Scenario I.*

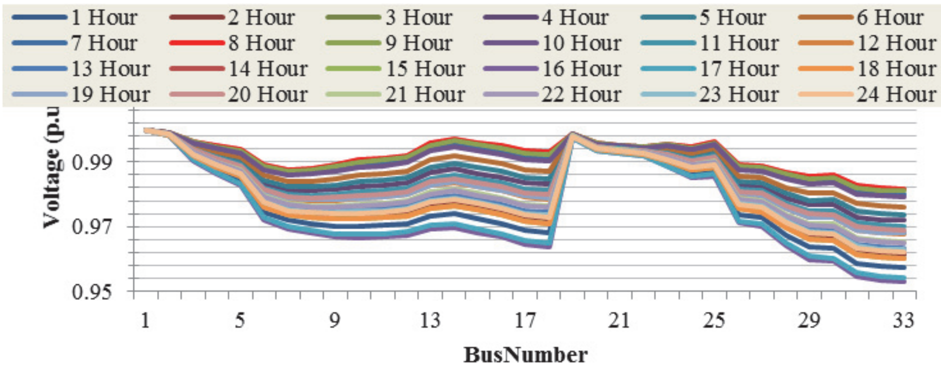

Fig. 3 – *Voltage Profile improvement of 33 bus system for Scenario II.*

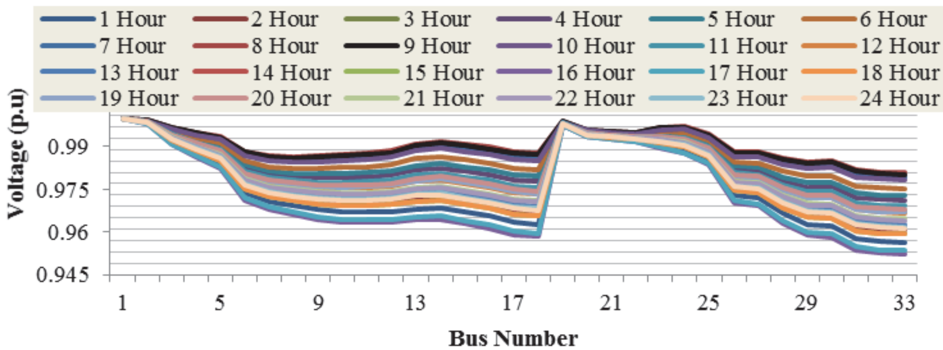

Fig. 4 – *Voltage Profile improvement of 33 bus system for Scenario III.*

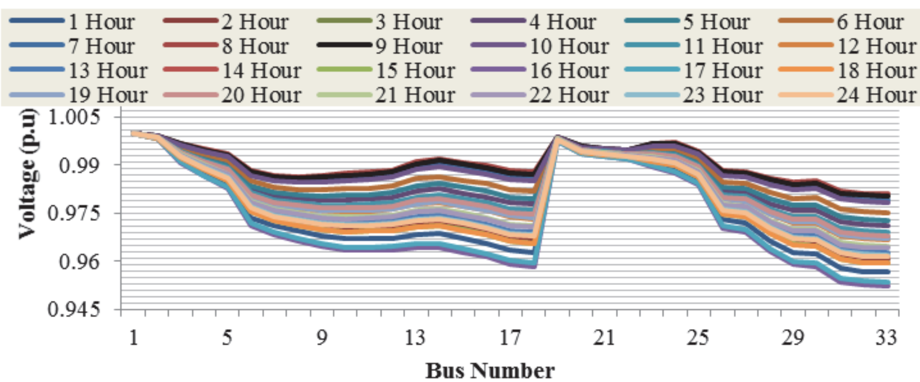

Fig. 5 – *Voltage Profile improvement of 33 bus system for Scenario IV.*

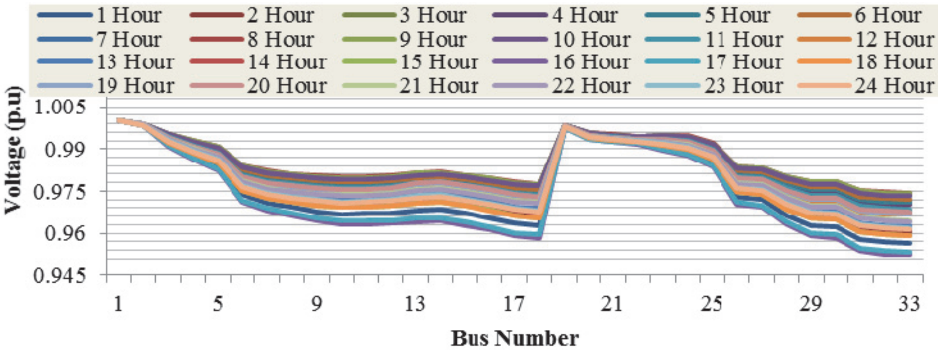

Fig. 6 – *Voltage Profile improvement of 33 bus system for Scenario V.*

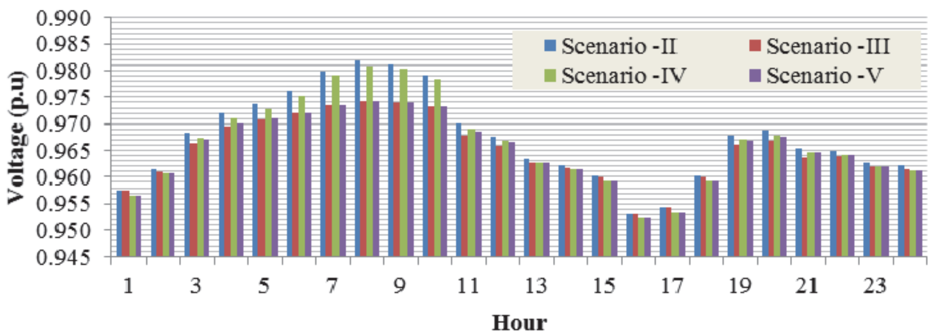

Fig. 7 – *Voltage Profile of all scenarios for 33 Bus System with AQiEA.*

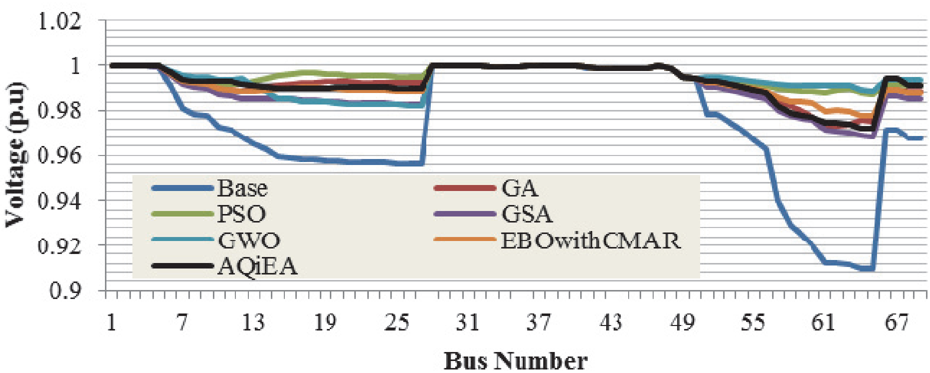

Fig. 8 – *Voltage Profile improvement of 69 bus system for Scenario I.*

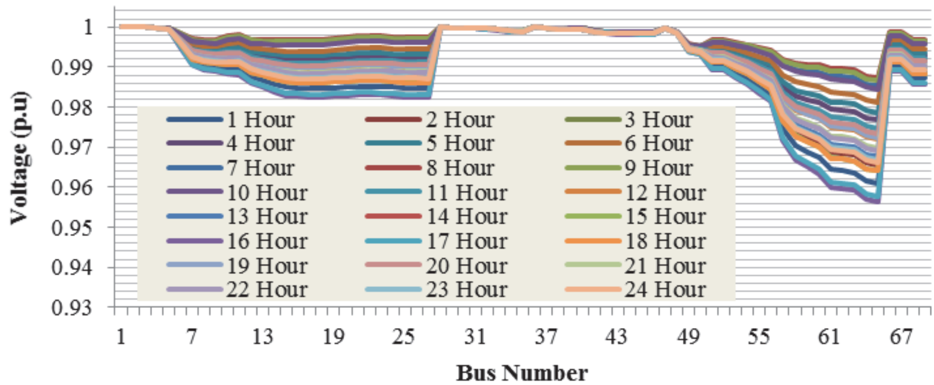

Fig. 9 – *Voltage Profile improvement of 69 bus system for Scenario II.*

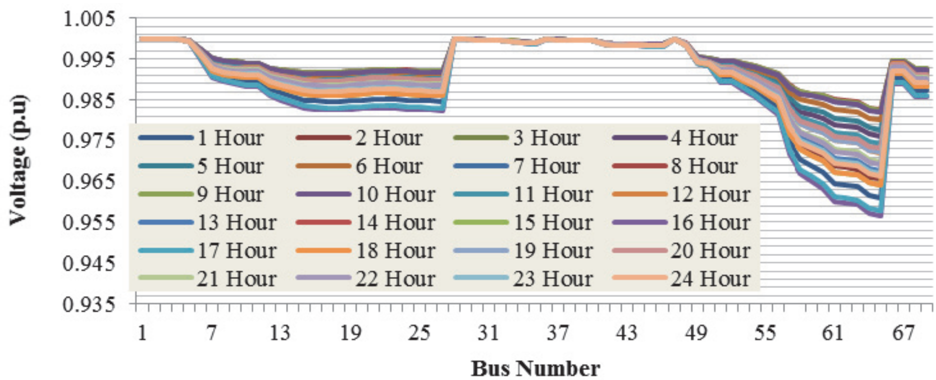

Fig. 10 – *Voltage Profile improvement of 69 bus system for Scenario III.*

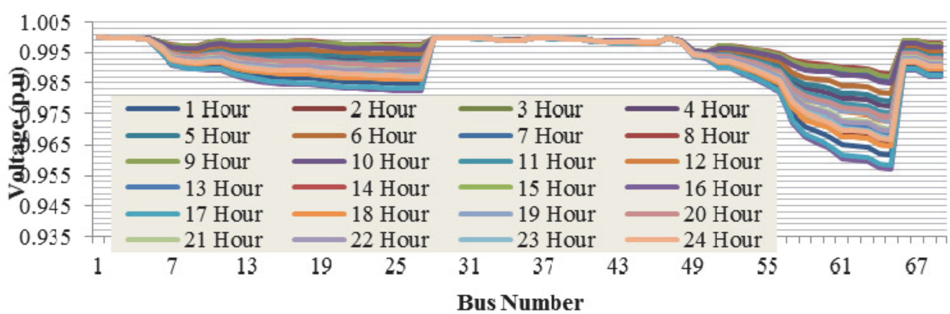

Fig. 11 – *Voltage Profile improvement of 69 bus system for Scenario IV.*

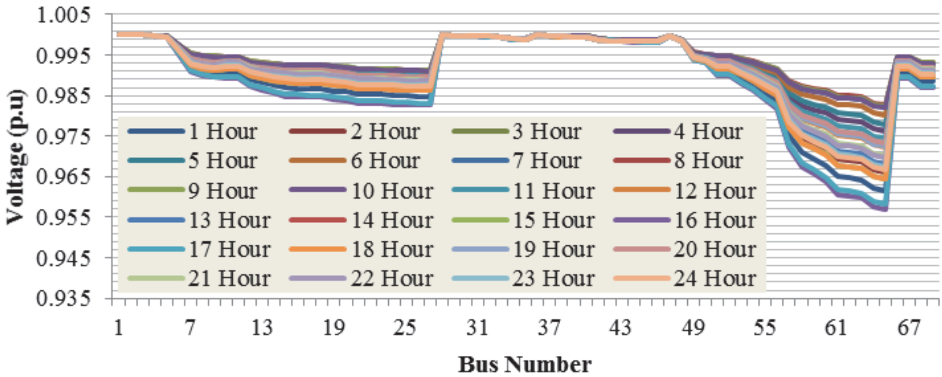

Fig. 12 – *Voltage Profile improvement of 69 bus system for Scenario V.*

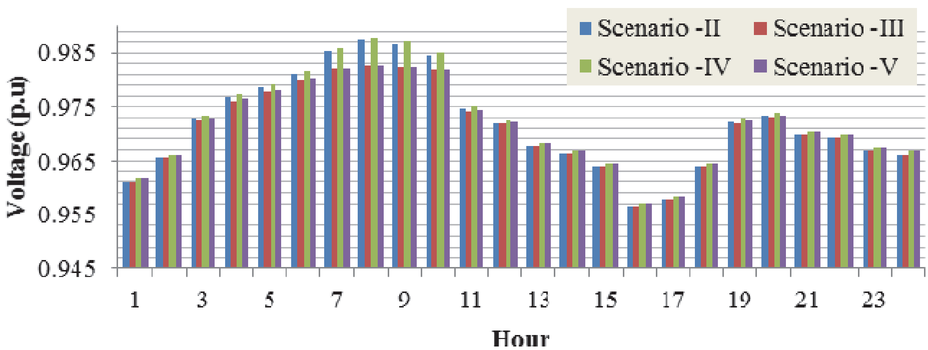

Fig. 13 – *Voltage Profile of all Scenarios for 69 Bus System with AQiEA.*

Maximum power loss reduction is obtained in Scenario V. In Scenario V, the load profile and DG locations are same as in Scenario IV, but the load allocation of DG is varied for every hour with maximum allowable size 1 MW, 1 MW, and 788 kW respectively. In Scenario IV, maximum utilization of DG is done as compared to other scenarios. Fig. 14 shows the complete analysis of power loss (Scenario I) and average power losses for twenty-four hours (i.e., Scenario II, Scenario III, Scenario IV, and Scenario V). Voltage profile improvement of the test bus system, i.e., 33 bus system for all scenarios is shown in Figs. 2 – 7.

Under normal operating condition viz., without DG in the distribution system, the overall active and reactive power losses are 202.62 kW and 135.3kVAr. **Table 3** shows the complete analysis of five different scenarios with average power loss for each scenario along with its standard deviation. Scenario V has a minimum average power loss of 73.266 kW followed by Scenario I, Scenario III, Scenario IV and Scenario II with average power losses as 74.12 kW, 74.77 kW, 75.12 kW and 76.098 kW respectively.

Table 2

33 Bus RDS performance analysis for the proposed method.

	Base Case	Scenario I	Scenario II
P_{loss} (kW)	202.62	73.39	75.36
Q_{loss} (kVAr)	135.22	50.61	51.92
P_{load} (MW)	3.715	1.03	1.03
Location	…..	25,14,30	25,14,30
Size/ Allocation (MW)	…..	0.768, 0.9175, 1	0.768, 0.9175, 1
	Scenario III	**Scenario IV**	**Scenario V**
P_{loss} (kW)	74.02	73.72	73.26
Q_{loss} (kVAr)	50.76	50.81	50.42
P_{load} (MW)	1.18	0.93	1.01
Location	25,14,30	30,24,14	30,24,14
Size/ Allocation (MW)	0.768,0.9175, 1	1,1, 0.7885	1, 1, 0.7885

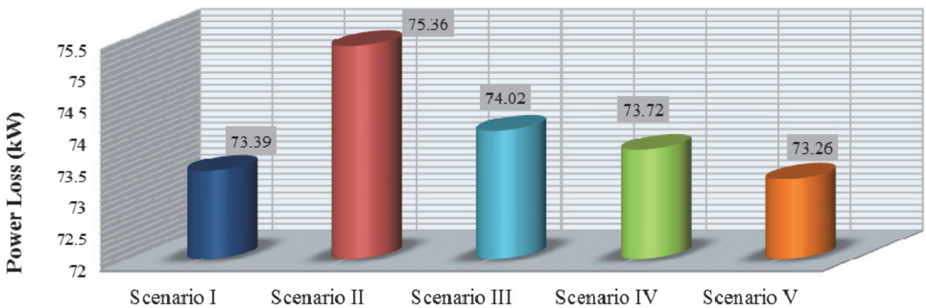

Fig. 14 – *Power loss for 33 bus RDS at five different Scenarios.*

Table 3

33 Bus RDS performance analysis for the proposed method.

	Scenario I	Scenario II	Scenario III	Scenario IV	Scenario V
Average (kW)	74.1207	76.0982	74.7786	75.1290	73.2660
Standard Deviation	0.7089	0.7172	16.1955	0.7139	15.7914

Table 4 shows the comparative analysis between different scenarios using the Wilcoxon signed rank test [31 – 32]. Let R^+ be the sum of ranks for the function on which the first scenario either outperformed on the other scenario or

performed as good as the other scenario and R$^-$ be the sum of ranks for the opposite case. The computed P_{value} for all the pairwise comparison is lower than 0.05, i.e., level of significance. So all the Null hypothesis in **Table 4** are rejected.

Table 4

Wilcoxon signed rank test for 33 bus system.

Comparison	R^+	R^-	P_{Value}	*Hypothesis*
Scenario I vs. Scenario II	0	465	0	$H_0: \mu_{scenario-I} \geq \mu_{scenario-II}$ $H_1: \mu_{scenario-I} < \mu_{scenario-II}$
Scenario II vs. Scenario III	465	0	0	$H_0: \mu_{scenario-III} \geq \mu_{scenario-II}$ $H_1: \mu_{scenario-III} < \mu_{scenario-II}$
Scenario III vs. Scenario IV	119	346	0.012	$H_0: \mu_{scenario-IV} \geq \mu_{scenario-III}$ $H_1: \mu_{scenario-IV} < \mu_{scenario-III}$
Scenario IV vs. Scenario V	465	0	0	$H_0: \mu_{scenario-V} \geq \mu_{scenario-IV}$ $H_1: \mu_{scenario-V} < \mu_{scenario-IV}$

69 bus system:

In Scenario I, real power losses are reduced to minimum value by optimally placing and sizing the DG at locations 61, 22, 66 with DG size 1.5 MW, 340 kW, and 640 kW respectively. Single hour load data in Scenario I is converted into twenty-four hour load data by mapping as given in the Appendix. Scenario III is the same as Scenario II; however, in Scenario III, load allocation on the three DGs is varied for every hour within maximum allowable size 1.5 MW, 340 kW, and 640 kW respectively.

The power losses obtained in Scenario IV has lesser value as compared to Scenario II and Scenario III. **Table 5** shows that Scenario IV is producing lesser power losses by placing and sizing DG at 17, 11, 61 and 373 kW, 697 kW, 1.5 MW as compared with Scenario III, and Scenario II. Maximum power loss reduction is obtained in Scenario V, except for Scenario I. Scenario V has same load profile and DG locations as Scenario IV, but in Scenario V the load allocation on DGs is varied for every hour within the maximum allowable size 373 kW, 697 kW, and 1.5 MW respectively. In Scenario IV, maximum utilization of DG is done as compared to other scenarios due to the optimization of DG (location and size) is done for the entire period of twenty-four hours. Fig. 15 shows the complete analysis of power loss (Scenario I) and average power losses for twenty-four hours (i.e., Scenario II, Scenario III, Scenario IV, and Scenario V).

Initial active and reactive power losses in the network without DG are 224.9 kW and 102.12 kVAr respectively. **Table 6** shows the comparative study of all the scenarios on the power losses using AQiEA for the 69 bus system. Scenario II has high average power loss as compared to other scenarios. These high power losses in Scenario II is due to the fixed location and size of DGs. The overall active power losses in all the scenarios are calculated for twenty-four hours period except for Scenario I. Tabulated results show that Scenario V has a maximum reduction in power loss as compared with other scenarios. Voltage profile improvement of the test bus system, i.e., 69 bus system for all scenarios is shown in Figs. 8 – 13.

Table 5

69 Bus RDS performance analysis for the proposed method.

	Base Case	Scenario I	Scenario II
P_{loss} (kW)	202.62	71.495	73.676
Q_{loss} (kVAr)	135.22	35.76	36.75
P_{load} (MW)	3.715	1.32	1.32
Location	…..	61, 22, 66	61, 22, 66
Size/ Allocation (MW)	…..	1.5, 0.34, 0.64	1.5, 0.34, 0.64
	Scenario III	**Scenario IV**	**Scenario V**
P_{loss} (kW)	73.404	73.204	72.831
Q_{loss} (kVAr)	36.67	36.55	36.43
P_{load} (MW)	1.41	1.24	1.34
Location	61, 22, 66	17, 11, 61	17, 11, 61
Size/ Allocation (MW)	1.5, 0.34, 0.64	0.373, 0.697, 1.5	0.373, 0.697, 1.5

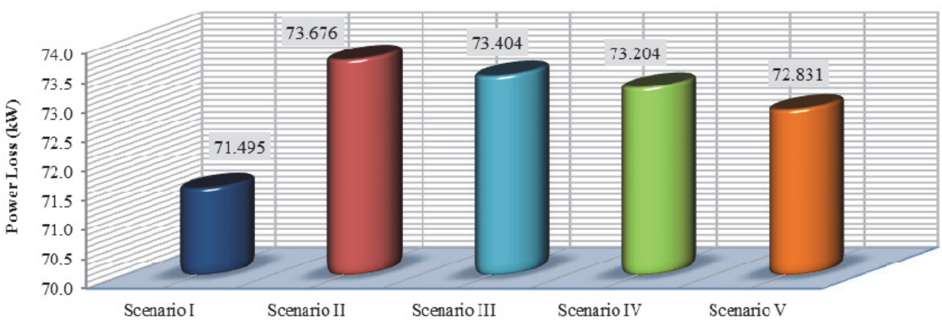

Fig. 15 – *Power loss for 69 bus RDS at five different Scenarios.*

Table 6

69 Bus RDS performance analysis for the proposed method.

	Scenario I	Scenario II	Scenario III	Scenario IV	Scenario V
Average (kW)	74.6475	76.7521	75.9304	76.5991	74.0344
Standard Deviation	0.1609	0.1628	16.6748	0.5548	16.0935

Table 7 shows, Wilcoxon signed rank test results between different scenarios for the 69 bus system. As the table states, Scenario I, Scenario II, Scenario III, and Scenario IV outperforms against Scenario II, Scenario III, Scenario IV, and Scenario V respectively, with the level of significance $a = 0.05$. Hypothesis associated with them is rejected, as computed P_{value} is less than the level of significance.

Table 7

Wilcoxon signed rank test for 69 bus system.

Comparison	R^+	R^-	P_{Value}	*Hypothesis*
Scenario I vs. Scenario II	0	465	0	$H_0:\ \mu_{scenario-I} \geq \mu_{scenario-II}$ $H_1:\ \mu_{scenario-I} < \mu_{scenario-II}$
Scenario II vs. Scenario III	465	0	0	$H_0:\ \mu_{scenario-III} \geq \mu_{scenario-II}$ $H_1:\ \mu_{scenario-III} < \mu_{scenario-II}$
Scenario III vs. Scenario IV	38	427	0	$H_0:\ \mu_{scenario-IV} \geq \mu_{scenario-III}$ $H_1:\ \mu_{scenario-IV} < \mu_{scenario-III}$
Scenario IV vs. Scenario V	465	0	0	$H_0:\ \mu_{scenario-V} \geq \mu_{scenario-IV}$ $H_1:\ \mu_{scenario-V} < \mu_{scenario-IV}$

Case B

It is observed from **Table 8**; the proposed algorithm has a higher reduction in power loss as compared with other algorithms. The average power losses for AQiEA is 72.37 kW followed by EBOwithCMAR, GWO, PSO, GA and GSA with losses 72.59 kW, 75.04 kW, 77.05 kW, 77.25 kW, and 85.01 kW respectively. Wilcoxon signed rank test is used for individual comparison between AQiEA and other algorithms. From **Table 9**, computed P_{value} is less than the level of significance $a = 0.05$ due to which the null hypothesis for each case is rejected.

Table 8

Comparative analysis of AQiEA with other algorithms for 33 bus system.

	GA	GSA	PSO	GWO	EBOwithCMAR	AQiEA
Average (kW)	77.2579	85.0131	77.0527	75.0452	72.5932	72.37619
Standard Deviation	0.6269	3.4801	1.7965	0.8684	0.566386	0.42686

Table 9

Wilcoxon signed rank test of aqiea for 33 bus system.

AQiEA vs	R^+	R^-	P_{Value}	*Hypothesis*
GA	0	465	0	$H_0:\ \mu_{AQiEA} \ge \mu_{GA}$ $H_1:\ \mu_{AQiEA} < \mu_{GA}$
PSO	0	465	0	$H_0:\ \mu_{AQiEA} \ge \mu_{PSO}$ $H_1:\ \mu_{AQiEA} < \mu_{PSO}$
GWO	0	465	0	$H_0:\ \mu_{AQiEA} \ge \mu_{GWO}$ $H_1:\ \mu_{AQiEA} < \mu_{GWO}$
GSA	0	465	0	$H_0:\ \mu_{AQiEA} \ge \mu_{GSA}$ $H_1:\ \mu_{AQiEA} < \mu_{GSA}$
EBOwithCMAR	121	344	0.0109	$H_0:\ \mu_{AQiEA} \ge \mu_{EBOwithCMAR}$ $H_1:\ \mu_{AQiEA} < \mu_{EBOwithCMAR}$

69 bus system

Table 10 shows the comparative analysis of the proposed algorithm with the existing algorithms. GA has a minimum reduction in power loss followed by GSA, GWO, PSO, EBOwithCMAR, and AQiEA. **Table 11** shows, the pairwise comparison of AQiEA with other algorithms. AQiEA shows significant improvement over GA, GSA, GWO, PSO, and EBOwithCMAR with the level of significance $a = 0.05$.

Table 10

Comparative analysis of AQiEA with other algorithms for 69 bus system.

	GA	GSA	PSO	GWO	EBOwithCMAR	AQiEA
Average (kW)	78.9656	78.024	75.0959	75.72	74.108	73.8007
Standard Deviation	2.6291	2.8677	1.3334	1.3207	0.8307	0.7599

Table 11

Wilcoxon signed rank test of AQiEA for 69 bus system.

AQiEA vs	R^+	R^-	P_{Value}	Hypothesis
GA	0	465	0	$H_0: \mu_{AQiEA} \geq \mu_{GA}$ $H_1: \mu_{AQiEA} < \mu_{GA}$
PSO	47	418	0	$H_0: \mu_{AQiEA} \geq \mu_{PSO}$ $H_1: \mu_{AQiEA} < \mu_{PSO}$
GWO	34	431	0	$H_0: \mu_{AQiEA} \geq \mu_{GWO}$ $H_1: \mu_{AQiEA} < \mu_{GWO}$
GSA	8	457	0	$H_0: \mu_{AQiEA} \geq \mu_{GSA}$ $H_1: \mu_{AQiEA} < \mu_{GSA}$
EBOwithCMAR	136	329	0.0236	$H_0: \mu_{AQiEA} \geq \mu_{EBOwithCMAR}$ $H_1: \mu_{AQiEA} < \mu_{EBOwithCMAR}$

Table 12 shows the parameters of different algorithms. Convergence graph for the proposed algorithm with GA, GSA, GWO, PSO, and EBOwithCMAR for both test bus systems are shown in Figs. 16 and 17.

Table 12

Parameter for different algorithm 'State of art' technique.

GA	**PSO**	**GWO**	**GSA**	**EBOwithCMAR**	**AQiEA**
Population Size =50	Population Size=50	Number of Agents N=50	Number of Agents N=50	$PS_{1,\max} = 18D$ $PS_{1,\min} = 4$	Population Size=50
Number of Generations =100	Acceleration factor C_1=C_2=2			$PS_{2,\max} = 46,8D$ $PS_{2,\min} = 10$ $PS_3 = 4 + (3\log(D))$	
Mutation probability = 0.02		$Iter_{max}$=200	$Iter_{max}$=200		$Iter_{max}$=200
Crossover probability =0.8	Inertia weights W_{max}=0.9 W_{min}=0.4			$CS = 100$ $prob_{is} = 0.1$ $cfe_{is} = 0.25FE_{\max}$	

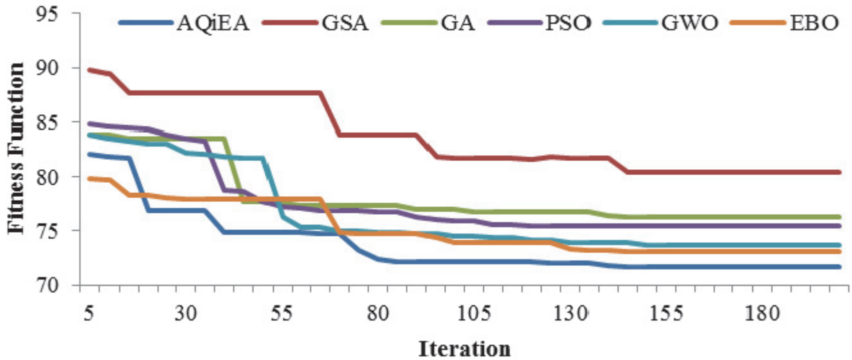

Fig. 16 – *Convergence Graph for 33 Bus System.*

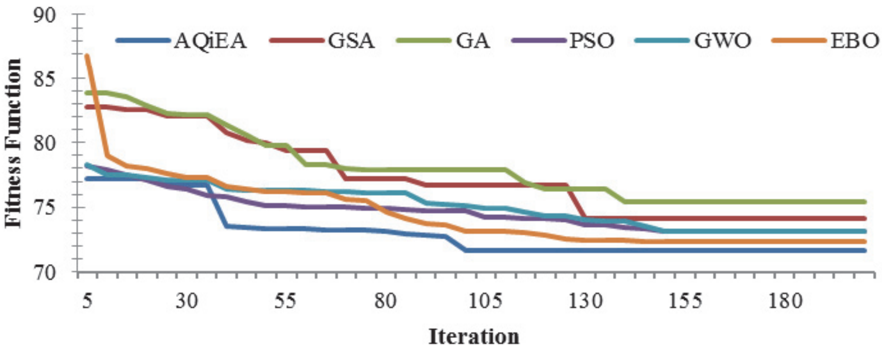

Fig. 17 – *Convergence Graph for 69 Bus System.*

Discussions:

Minimization of power losses in the distribution system is considered as one of the major concerns for the distribution utilities. Distribution systems have high admittance ratio, the power losses (both technical and non-technical losses) obtained in the distribution system are high in comparison with generation and transmission system. In order to minimize the power losses DGs are used as one of the alternative technique, many researchers had studied this combinatorial optimization problem with different analytical and metaheuristic techniques. In this paper, a novel methodology, i.e., five different scenarios are used to minimize the power losses with twenty-four hours load profile. In Scenario I, the power losses in the distribution system are minimized by placing and sizing the DG for a single hour load, which is a standard test case available in the literature.

The load at the distribution system is not fixed, and it varies during the day, so a single hour load cannot approximate twenty-four hours load profile. A novel methodology is used to minimize the power losses in the distribution system on a time horizon of twenty-four hours. In the appendix, a detailed description has been provided, regarding how the single hour power load is converted into a twenty-four hours load profile. In Scenario II, a twenty-four hours load profile is used as it is a more realistic approach as compared to a single hour load. However, the location and capacity of DG are the same for every hour as determined in Scenario I. It is observed that the average power losses produced in Scenario II are high as compared with Scenario I, which is due to improper utilization of the total power injected by DG for a time-varying load profile. The fixed injection of power from DGs is causing more losses with the change in load during twenty-four hours period in Scenario II. The location of DG cannot be changed on an hourly basis; however, the output of DG can be changed according to load variation subject to a maximum limit of DG, provided DG is dispatchable. The average power losses produced in Scenario II are further reduced in Scenario III, the load allocated on DG is varied for every hour within its maximum capacity with fixed placement as determined in Scenario I. In Scenario III, minimum power losses are obtained by adequately utilizing the capacity of DG for every hour with respect to variation in load demand. Average power losses obtained in Scenario III are further reduced in Scenario IV. Scenario IV is similar to the Scenario I, but in Scenario IV the location and capacity of DGs are determined for twenty-four hour load profile whereas in Scenario I, the location and capacity of DG are determined for a single hour load. Computational problem of optimization in Scenario IV is twenty-four times more complex as compared to Scenario I because we have to run load flow for each hour as compared to a single load flow being executed in Scenario I, so comparatively it is a more challenging problem. In Scenario V, it is further observed that the power losses are reduced as compared to Scenario IV by keeping the location fixed as determined in Scenario IV but varying the load allocated on DGs subject to its maximum capacity for every hour. In Scenario V, minimum power losses are obtained by adequately utilizing the optimal capacity of DG for every hour with respect to change in the load demand. Thus optimal placement and size of DG obtained from Scenario IV can be used to further reduce losses by proper scheduling of DGs on hourly bases. The hourly scheduling of DGs is possible only if the DGs are dispatchable; however, if DGs are not dispatchable, then the losses would be higher. So dispatchable DGs would help reduce power losses as compared to non-dispatchable DGs. Thus it is recommended to procure dispatchable DGs while planning the induction of new DGs. AQiEA is used to find the appropriate location and capacity of DGs for a varying load with a time horizon of twenty-four hours. AQiEA is designed by adopting some concepts and principles of quantum computing such as quantum-inspired bits (*Q*-bits), quantum gates (*Q*-gates), superposition, entanglement, and measurement. It is used to overcome the limitations associated with EA. AQiEA uses probabilistic representation with *Q*-bit. *Q*-bit is defined as the smallest unit of information in a quantum computer. *Q*-bit representation has a better characteristic population diversity than other representations. AQiEA doesn't require additional operators like local search and mutation to improve the convergence rate and avoid the premature convergence. A Quantum Rotation inspired Adaptive Crossover operator is used as a variation operator, which is parameter free. Three rotation strategies (R-I, R-II, R-III) are employed as variation operators to move the search towards better solutions. The results of simulated experiments in the tables demonstrate that AQiEA is performing better in comparison with other algorithms (GA, PSO, GWO, EBOwithCMAR, and GSA), which are available in the literature.

6 Conclusion

Placement and sizing of DG is a difficult combinatorial optimization problem. Many efforts have been reported in the literature for solving the critical problem. However, they have used benchmark problems with single hour load (fixed load). A novel methodology with two different test cases is adopted for minimization of power losses with five different scenarios on time horizon of twenty-four hours instead of a single hour load profile. If the location and capacity of DG is fixed for twenty-four hours, it was found that average power losses are higher as compared to the scenarios where load allocation on DGs was varied with change in load profile. It was concuded that the losses can be reduced by dynamic load allocation on Dispatchable DGs. Wilcoxon signed rank test is used to prove that difference in reduction of power loss is statistically significant. AQiEA is used to minimize the power losses by locating DGs at an optimal location with the appropriate size. It is tested on two test bus systems, i.e., 33 bus system and 69 bus system respectively. AQiEA uses two *Q*-bits instead of one *Q*-bit, which does not require any tuning of parameters and uses an adaptive quantum-based crossover operator. The performance of the proposed algorithm has been compared with the existing 'State of Art' techniques. The results show that the performance of the proposed algorithm is better as compared with other algorithms.

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8 Appendix

A new test instance is formulated by mapping the data for one hour load into twenty-four hours. The load curve for twenty-four hours for 33 bus system is shown in Fig. (A.1). The complete load data for twenty-four hours is shown in **Table A1**. $L_1, L_2, \ldots, L_{24}$ are the load at each hour for twenty-four hours. For N_b bus system the load at hour k is evaluated as follows:

$$L_k = \sum_{m=1}^{N_b} A_k \times P_m \ . \tag{A1}$$

Table A1

Load data for twenty-four hour for 33 bus system.

Hour	1	2	3	4	5	6
MW	4.16	3.98	3.67	3.50	3.43	3.31
MVAr	2.58	2.46	2.27	2.17	2.12	2.05
A_k	1.120	1.070	0.988	0.943	0.922	0.892
Hour	7	8	9	10	11	12
MW	3.14	3.05	3.08	3.17	3.59	3.70
MVAr	1.94	1.89	1.91	1.96	2.22	2.29
A_k	0.845	0.821	0.829	0.853	0.967	0.996
Hour	13	14	15	16	17	18
MW	3.89	3.94	4.04	4.35	4.30	4.04
MVAr	2.41	2.44	2.50	2.69	2.66	2.50
A_k	1.047	1.062	1.087	1.171	1.157	1.087
Hour	19	20	21	22	23	24
MW	3.69	3.65	3.80	3.82	3.92	3.95
MVAr	2.28	2.26	2.35	2.37	2.43	2.44
A_k	0.993	0.982	1.022	1.029	1.056	1.062

A_k is the rationalized constant which is fixed for N_b bus system for a particular hour load as given in **Tables A1** and **A2.** L_{av} is the average load of the system for twenty-four hour, which is equal to the fixed load for a single hour case.

$$L_{avg} = \frac{1}{24}\sum_{k=1}^{24} L_k \,. \tag{A2}$$

The total load on the system for the first hour is computed as follows:

$$L_1 = \sum_{m=1}^{N_b} A_1 \times P_m \,. \tag{A3}$$

Similarly, the total load on the system at the 24th hour is given as follows:

$$L_{24} = \sum_{m=1}^{N_b} A_{24} \times P_m \,. \tag{A4}$$

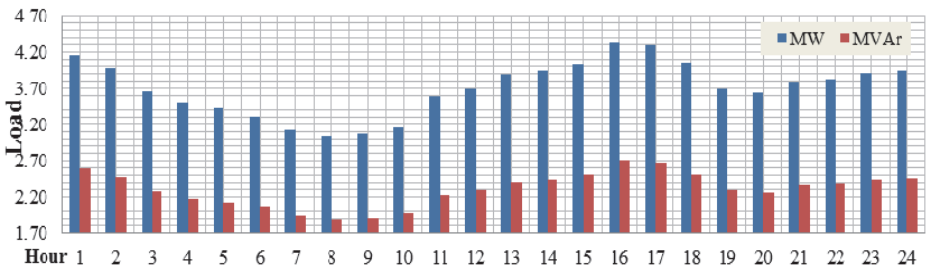

Fig. A.1 – *33 bus system load for twenty-four hour.*

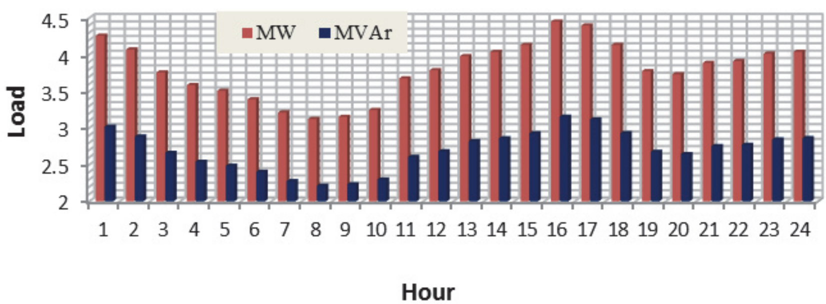

Fig. A.2 – *69 bus system load for twenty-four hour.*

The real and reactive power load of 33 bus system is 3.175 MW and 2.3 MVAr. Fig. A1 shows the graphical representation of load for twenty-four hours for 33 bus system by mapping it. At every hour the load at 33 bus system is changing with respect to their demand at load centers.

The real and reactive power load of the 69 bus system is 3.801 MW and 2.694 MVAr. Fig. A2 shows the graphical representation of load for twenty-four hours for 69 bus system by mapping it. At every hour the load at 69 bus system is changing with respect to their demand at load centers.

Table A2

Load data for twenty-four hour for 69 bus system.

Hour	1	2	3	4	5	6
MW	4.26	4.07	3.76	3.58	3.51	3.39
MVAr	3.02	2.88	2.66	2.54	2.48	2.40
A_k	1.120	1.070	0.988	0.943	0.922	0.892
Hour	7	8	9	10	11	12
MW	3.21	3.12	3.15	3.24	3.68	3.79
MVAr	2.28	2.21	2.23	2.30	2.60	2.68
A_k	0.845	0.821	0.829	0.853	0.967	0.996
Hour	13	14	15	16	17	18
MW	3.98	4.04	4.13	4.45	4.40	4.13
MVAr	2.82	2.86	2.93	3.15	3.12	2.93
A_k	1.047	1.062	1.087	1.171	1.157	1.087
Hour	19	20	21	22	23	24
MW	3.77	3.73	3.89	3.91	4.01	4.04
MVAr	2.67	2.64	2.75	2.77	2.84	2.86
A_k	0.993	0.982	1.022	1.029	1.056	1.062