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ORIGINAL PAPER

Enhancement of performance indices on realistic load models with distributed generators in radial distribution network

Gopisetti Manikanta[1] · **Ashish Mani**[1] · **Hemender Pal Singh**[1] · **Devendra Kumar Chaturvedi**[2]

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Abstract

The location and capacity of Distributed Generators (DG) are the two crucial factors that play a vital role in distribution networks towards reducing power losses. Independent implementation of DG injects either active power or reactive power and has attracted the interest of many researchers. However, some researchers have studied this important optimization problem with constant power load model or with the independent implementation of voltage dependent load models. In practical distribution network, loads provided by distribution utilities are mostly ZIP load models. So it is necessary to study the effect of DG on ZIP loads in distribution system to reduce power losses. In this study, an investigation has been performed to observe the effect of ZIP load models on the implementation of DG. The main objective of the study is to reduce the power losses with the implementation of DG considering ZIP load models. In this study, two cases are investigated to reduce the power losses with different scenarios. In Case-A, ten different scenarios are considered to study the effect of ZIP load model on the implementation of DG. Seven different independent ZIP load models have been proposed to study the effect of DG with different performance indices such as real power loss index (RPLI), the reactive power loss index (RePLI), voltage deviation index (VDI) and the real power injected by DG (P_{DG}). Optimal placement and sizing of DG is a difficult non linear combinatorial optimization problem. Many evolutionary algorithms have been used to reduce the power losses with independent implementation of DG. However, evolutionary algorithms often suffer from some limitations, so quantum inspired evolutionary algorithm (QiEA) is used to overcome these limitations. An adaptive quantum inspired evolutionary algorithm (AQiEA) which is the updated version of QiEA is used to find the optimal location and capacity of DG. In Case-B, effectiveness of the proposed algorithm is tested on two IEEE benchmark test bus system with three different Scenarios. Multi objective function is formulated with real power loss, reactive power loss, voltage deviation index, and total power injected by DG. Tabulated results demonstrate that AQiEA is performing better in all aspects such as real power loss, active

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power injected by DG & percentage power loss reduction as compared with Particle Swarm Optimization (PSO), Symbiotic Organism Search (SOS), Jaya Optimization (JO), Ant Lion Optimization (ALO) and Dragon Fly Optimization (DFO).

Keywords Realistic load models · ZIP load models · Distributed generator · Performance indices · AQiEA · Power losses

List of symbols

$\%P_{loss}$	Percentage reduction in power loss
$\%P_{DG}$	Total percentage of active power injection with DG
n	Number of DGs
$P_0 \& Q_0$	Real and reactive powers at rated voltage (V_0)
P_{DG}	Total power injected by DG
$P_{DG}^{min} \& P_{DG}^{max}$	Minimum and maximum allowable size of DG
P_{Load}	Active power load in the system
$P_l(m)$	Power injected by DG at particular bus 'm'
P_{loss}	Total active power loss
P_{lswDG}	Active power loss with DG
P_{lswoDG}	Active power loss without DG
Q_{loss}	Total reactive power loss
Q_{lswDG}	Reactive power loss with DG
Q_{lswoDG}	Reactive power loss without DG
$RPLI_{wDG}$	Real power loss index with DG
$RPLI_{woDG}$	Real power loss index without DG
$RePLI_{wDG}$	Reactive power loss index with DG
$RePLI_{woDG}$	Reactive power loss index without DG
VDI_{wDG}	Voltage deviation index with DG
VDI_{woDG}	Voltage deviation index without DG
Z_p, I_p, P_p	ZIP coefficients of real power
Z_q, I_q, P_q	ZIP coefficients of reactive power
$P \& Q$	Real and reactive power operating at voltage (V_i)

Abbreviations

ABC	Artificial bee colony algorithm
AC	Air conditioner
ALO	Ant lion optimization
AQiEA	Adaptive quantum inspired evolutionary algorithm
BPSO-SLFA	Binary particle swarm optimization and shuffled frog
DFO	Dragonfly optimization
DG	Distributed generator
EHOA	Elephant herding optimization algorithm
GA	Genetic algorithm
IL	Incandescent light
JO	JAYA optimization
LED	LED light

MOF	Multi objective function
MRFO	Manta ray foraging optimization algorithm
MWe	Microwave
PC	Personal computer (monitor and CPU)
PSO	Particle swarm optimization
QiEA	Quantum inspired evolutionary algorithm
Refg	Refrigerator
SKHA	Stud krill herd algorithm
SOS	Symbiotic organism search
VCm	Vacuum cleaner
VDI	Voltage deviation index
WOA	Whale optimization algorithm
ZIP load	Constant impedance (Z), constant current (I) and constant power load

1 Introduction

The load composition in distribution network is changing over past few years and also load at distribution network is increasing day by day due to the technological advancements. Over past few years, there is proliferation of electronic supplies in many households such as laptops, cell-phone chargers, fluorescent compact lights (CFLs) and flat screen TVs [1]. Similarly in case of lighting industry, there is rapid change in ballast technology. In recent times, electronic ballast (constant power load) is mostly used as compared to magnetic ballasts (constant impedance load). In present scenario, new lights i.e., [light-emitting diode (LED) lights and induction lights] are introduced into the market which creates a major change in the lighting industry due to its better efficiency [2]. In distribution network, two approaches are mainly used to build the loads, viz., measurement based method [3] and component based method [4]. Traditional power system analysis tool often use voltage dependent load models i.e., the load which varies with square of voltage and linear with voltage. These are constant impedance load (CZ), constant current load (CI) and constant power load (CP) namely ZIP load model [5]. The main objective of the study is to present a realistic ZIP load model in distribution network. An investigation has been done to reduce the power losses with implementation of DG on different ZIP load models. In addition to power loss minimization, performance indices are also analyzed to study the effect with DG on different ZIP load models.

Distribution network acts as main link in power system which has very significant importance. It acts as an end link to transfer power from transmission system to consumers. The main aim of distribution companies is to provide efficient power with minimum power losses and improved voltage profile. However, distribution network has high power losses as compared with transmission system because of its high resistance to reactance ratio. The node voltage of the system is reduced as it moves away from the substation or reference node. So in order to reduce the power losses and improve the voltage profile, there is always a demand for power compensation. In recent times, DGs are mainly used in distribution network to reduce the power losses [6]. DG is defined as the small scale power generating source that is placed nearer to load centers, which reduces the transmission cost and minimizes the power losses in power delivery. DG size generally varies from few kW to several MW. In this study, real power injection i.e., DG which injects only real power into the system is studied, which reduces the load burden in the system. Reduction in energy loss, improvement in stability, power factor, voltage profile and reduction in peak demand are some advantages of placing DG at optimal location with optimal size. Optimal location and capacity of DG are two key important factors which play important role in distribution system to reduce the power losses. DGs are generally classified into two types viz., one is conventional and the other is non-conventional energy sources. In present scenario, there is depletion in conventional energy sources, and non-conventional energy resources have gained more importance due to their numerous advantages.

Optimal location and capacity of DG are two key important factors which play a major role to reduce the power losses. Many researchers have solved the optimal location and capacity of DG optimization problem with analytical and metaheuristic techniques. Viral and Khatod [7] proposed an analytical method to find the optimal location and sizing of DG. The main objective of the study was to reduce the losses with implementation of DG. The optimal location of DG is identified by sequence of nodes, whereas the optimal sizing is identified by optimizing the loss saving equation. Singh and Parida [8] used an analytical method to find the optimal location of DG. Two analytical methods such as Loss reduction sensitivity method and Voltage improvement sensitivity method are used to reduce the power losses and improve the voltage profile. Acharya et al. [9] proposed an analytical method to calculate the optimal size and location of DG, to minimize the power losses in radial distribution system. Alemi and Gharehpetian [10] used an analytical method to determine the optimal location and capacity of DG with an objective to improve the voltage profile and reduce the power loss. Loss sensitivity and priority list methods are used to find the location and size of DG.

Analytical methods are easy and simple to apply on small test bus systems with a single optimization objective. However, when the analytical techniques are applied on multi objective functions or large test bus systems, the computational burden becomes heavier and global optima are not guaranteed. Implementation of DG in distribution network to reduce the power losses is an interesting and challenging area of research where many researchers have used different techniques. In comparison with analytical techniques, metaheuristic techniques can provide competitive solutions at reduced computational burden. Thus, more metaheuristic techniques are implemented in distribution network to solve this complex combinatorial optimization problem. Metaheuristic techniques are principally population based optimization techniques which mainly work on Darwinian principle. Individuals in the population are competing with one another, best among them will move to the next generation. This natural selection often leads to better solutions. Some metaheuristic techniques which are mainly used to solve the optimal location and capacity of DG are Stud Krill herd Algorithm (SKHA) [11], JAYA Optimization algorithm (JO) [12], Binary Particle Swarm Optimization and Shuffled Frog Leap (BPSO-SLFA) algorithm [13], Dragonfly optimization algorithm (DFO) [14], Symbiotic organism search (SOS) [15], Whale optimization algorithm (WOA) [16], Particle Swarm Optimization (PSO) [17], Ant Lion Optimization (ALO) [18], Manta Ray Foraging Optimization algorithm (MRFO) [19], Elephant herding optimization algorithm (EHOA) [20], Genetic Algorithm (GA) [21] and Artificial bee colony (ABC) algorithm [22].

Chithra Devi et al. [11] used a new metaheuristic technique known as Stud Krill herd Algorithm (SKHA) to find the location and size of DG. The objective of study is to reduce the power losses with various constraints such as DG power injection, location constraint and voltage limit. Jain and Venkaiah [12] solved optimal location and sizing of DG problem with a Multi-Objective JAYA (MOJAYA) algorithm. The objectives of the study are stability of the system, voltage profile and reduction in the power losses. Hassan et al. [13] proposed a hybrid optimization algorithm i.e., Binary Particle Swarm Optimization and Shuffled Frog Leap (BPSO-SLFA) algorithm to determine the optimal placement and capacity of DG. Multi objective function is formulated to reduce the losses, improve the voltage and stability of the system. Suresh and Belwin [14] solved optimal location and capacity of DG problem with a nature inspired algorithm known as Dragonfly optimization algorithm (DFO). Different types of DGs which are operating on different power factors are considered to reduce the power losses. Reddy et al. [16] used Whale optimization algorithm (WOA) to improve the voltage and reduce the power losses. WOA is used to find the optimal size of DG and index vector method is used to determine the optimal location of DG.

Kanwar et al. [17] used Particle Swarm Optimization (PSO) technique to reduce the power losses with simultaneous implementation of DG operating in parallel with shunt capacitors and network reconfiguration. Reddy et al. [18] and Hemeida et al. [19] used different metaheuristic techniques [Ant Lion Optimization (ALO) and Manta Ray Foraging Optimization algorithm (MRFO)] to determine the location and capacity of DG. Reduction in power loss and improvement in voltage profile are main objectives considered in both studies. Prasad et al. [20] used a nature inspired algorithm known as Elephant herding optimization algorithm (EHOA) to determine the optimal size of DG to reduce the power losses. Optimal placement of DG is determined by power loss index method which reduces the search space. Prakash et al. [21] used well known algorithm i.e., Genetic Algorithm (GA) approach to find optimal placement and size of DG in distribution system to improve the voltage stability, voltage profile and minimize the power losses. Al-Ammar et al. [22] investigated the impact of DG on optimal location and capacity with a concept to reduce the energy cost along with voltage drop and power losses. Artificial bee colony (ABC) algorithm is used to find the optimal location and capacity of DG with multiple objectives. It has been observed from above studies that majority of authors have used constant power load model to reduce the power losses in distribution network. To the best of authors' knowledge, if the optimal location and capacity obtained with constant power load model is implemented in actual distribution network, it will induce more power losses and poor voltage regulation in the system because the load at distribution network is mainly dependent on magnitude of supply voltage.

Some authors have also solved the DG optimization problem with voltage dependent load model.

Kashyap et al. [23] used an analytical method for implementation of multiple DGs with ZIP load model. Simultaneous implementation of ZIP load and economic load growth for a specific period of time is investigated. An investigation has been proposed to study the effect of ZIP load models on different DGs to reduce the power losses and cost of energy loss. Murty and Kumar [24] used loss sensitivity analysis to determine the optimal location and capacity of Capacitor to reduce the power losses with ZIP load model. Economic load growth and winter load variations are considered in the study. However, the objectives of the study are to reduce the overall cost and loss savings per annum with optimal capacitor placement. Polisetti and Kumar [25] used optimal power flow approach with ZIP loads to determine the nodal price along with marginal clearing price by reducing the total operating cost in the system. El-Zonkoly [26] used particle swarm optimization method to find the optimal location and capacity of DG. Different load models are considered to study the effect of DG with different performance indices such as MVA intake by the grid, voltage profile and power losses in the system. Sadeghi and Kalantar [27] used priority list method to find the optimal location of DG. The main objective of the paper is to simulate and compare the results of DG allocation in a power system, when the loads at each bus are simulated with ZIP load model. Least square optimization technique is used to model the load as ZIP load. Murty and Kumar [28] used power loss sensitivity index-based approach to find the optimal location of Capacitor. Power loss index and index vector are also used for optimal location of Capacitor. The three sensitivity methods are used in the system to provide reactive power compensation and compared on cost saving, loss reduction, operating cost and total kVAr support.

Many analytical, heuristic and meta-heuristic techniques are used to solve this important optimization problem. Some authors have solved this important optimization problem with constant power load model. In actual practice, the load at distribution network is mainly dependent on magnitude of voltage because of change in impedance, power and current. The assumption of constant power load model i.e., which is independent of voltage, induces more power losses in the system due to improper placement and sizing of DG. It has been observed from above literature review that majority of authors have solved optimization of DG problem with either constant power load or with voltage dependent load model. The literature review reveals that static load models are more applicable in distribution system with respect to the load behavior. In general, there are three types of load models viz., constant power load (CP), constant impedance load (CZ) and constant current load (CI). Combination of all these loads represents a realistic static load model i.e., ZIP load model. In this study, an investigation has been proposed to study the effect of DG on realistic static load models. The main objective of the study is to reduce the power losses with implementation of DG on different ZIP load models. In addition to power losses, performance indices for different ZIP load models are also studied. Optimal location and capacity of DG involves combination of continuous and discrete variables. A quantum inspired evolutionary algorithm [29] is used to solve this difficult combinatorial optimization problem. Adaptive quantum inspired evolutionary algorithm [30] uses probabilistic representation with Q-bits. The proposed algorithm uses two Q-bits, which helps in improving the quantum search. The proposed algorithm has been applied in many engineering optimization problem [30–36], AQiEA performs well in all scenarios as compared with the other algorithms which are used in the study.

The main contributions of the paper are as follows.

1. The objective of the study is to reduce the power losses, an investigation has been performed to study the effect of DG with different realistic static load models i.e., seven different independent ZIP load models are considered.
2. A novel methodology has been proposed to find the location and capacity of DG. An AQiEA is used to solve the combinatorial optimization problem which involves continuous and discrete variables.
3. Performance indices such as real power loss index (RPLI), the reactive power loss index (RePLI), voltage deviation index (VDI) & the real power injected by DG (PDG) are also studied.
4. Multi objective function is formulated with real power loss, reactive power loss, voltage deviation index and total power injected by DG.

Minimization of power losses is one of the major concerns for distribution utilities, many techniques have been implemented in distribution system to reduce the power losses. In present scenario, DG has gained more importance in distribution system to reduce the power losses. However, many researchers have solved the optimization problem of placement and sizing of DG with different analytical and metaheuristic techniques with constant power load or single hour load. Constant power load doesn't vary with time and is also independent of voltage. It is well known that the load at distribution network mainly comprises of different loads. In practical distribution network, it has been observed that the consumer load at a specific bus or all buses uses combination of all voltage dependent load models i.e., mixed load model. However combination of all voltage dependent load models at specific bus or all buses has not been studied adequately. In this study, an investigation has been proposed to study the effect of DG on realistic static load models. In addition to power losses, performance indices for different ZIP load models are also studied.

Rest of the paper is organized as follows, "Problem formulation" section describe the objective to minimize the power loss by implementation of DG with different ZIP load models in distribution system. Placement and sizing of DG is a difficult non differentiable combinatorial optimization problem. A quantum inspired evolutionary optimization algorithm has been used to solve the optimization problem of DG, which has been explained in section 'Algorithm'. The effectiveness of AQiEA is compared with other algorithms has been shown in 'Results and Discussions' section. Finally, the findings of the paper is presented in 'Conclusions' section.

2 Problem formulation

2.1 Objective function

The main objective of the study is to reduce the power losses with implementation of DG on different ZIP load models. The individual power loss obtained at each branch section and overall power losses are calculated as follows.

$$\text{Min.}\left\{ \mathrm{P}_{loss} = \sum_{m=1}^{N_b} I_m^2 \times R_m \right\}. \tag{1}$$

2.2 Distributed generator

Optimal location and capacity of DG not only reduces the power losses and but also improves the voltage profile in the system. Power injected by DG at a particular bus m is given as follows.

$$P_L(m) = P_L(m) - P_{DG}(m) \tag{2}$$

Constraints for power loss minimization with DG are given as follows:

(a) Operation of distributed generator:

Improper placement and sizing of DG induces more power losses in the system with poor voltage regulation. In some case it may damage the system equipment, it is necessary that power injected by DG have always been in acceptable limits.

$$P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max}. \tag{3}$$

(b) Power injection for the system:

DGs are placed nearer to load centers, if DG induces high power into the system i.e., greater than total power demand and losses, bi directional power flow may damage the system equipment. It is necessary that, total power injected by DG always less than demand and losses in the system.

$$\sum_{i=1}^{n} P_{DG,i} \le P_{demand} + P_{loss} \tag{4}$$

(c) Power injection:

Total power injected by distributed generator and substation has to meet the demand at load centers including power losses.

$$P_{SubStation} + \sum_{i=1}^{n} P_{DG,i} = P_{demand} + P_{loss} \tag{5}$$

2.3 ZIP load models

In distribution network, load composition has subsequently changed in last few years. Over past few years, the appliances used in the household [for example: laptop cell-phone chargers, fluorescent compact lights (CFLs), and flat screen TVs], has modified the over all load composition. In this study a realistic load model is considered which represents the polynomial equation of voltage magnitude on power–voltage relationship. The objective of the paper is to study the effect of DG on ZIP load models. Where ZIP represents constant impedance load (CZ), constant current load (CI) and constant power load (CP) respectively. The expressions for real and reactive powers of the ZIP coefficients model are

$$P = P_0 \left[Z_p \left[\frac{V_i}{V_o} \right]^2 + I_p \left[\frac{V_i}{V_o} \right] + P_p \right], \tag{6}$$

$$Q = Q_0 \left[Z_q \left[\frac{V_i}{V_o} \right]^2 + I_q \left[\frac{V_i}{V_o} \right] + P_q \right], \tag{7}$$

where $Z_p + I_p + P_p = 1\&Z_q + I_q + P_q = 1$.

In conventional power flow studies, constant power load model is considered with ZIP coefficients are zero. The coefficients of ZIP load model are given in Table 1.

2.4 Performance indices

The effect of DG on ZIP load models are studied with different performance indices. The performance indices with DG are given below.

Table 1 Real and reactive ZIP load models

Scenario	Components	Real power (P)			Reactive power (Q)		
		Z_p	I_p	P_p	Z_q	I_q	P_q
1	Air conditioner	1.60	– 2.69	2.09	12.53	– 21.10	9.58
2	Incandescent lamp	0.54	0.50	– 0.04	0.46	0.51	0.03
3	LED light	0.58	1.13	– 0.71	1.78	– 0.80	0.02
4	Microwave	– 0.27	1.16	0.11	15.64	– 27.7	13.10
5	Vacuum	0.92	0.07	– 0.01	0.91	– 0.02	0.11
6	PC	0.18	– 0.26	1.08	– 0.19	0.96	0.23
7	Refrigerator	1.19	– 0.26	0.07	0.59	0.65	– 0.24

Real power loss index (RPLI): It is defined as the ratio between the real power losses induced in the system without placing DG to after implementation of DG i.e., ratio between P_{loss} with DG to the P_{loss} without DG.

$$RPLI = \frac{P_{lswDG}}{P_{lsw0DG}} \times 100. \quad (8)$$

The lower the value of the index indicates the better in terms of reduction in power loss with optimal location and capacity of DG.

Reactive Power Loss Index (RePLI): It is defined as the ratio between the reactive power losses induced in the system without placing DG to after implementation of DG i.e., ratio between Q_{loss} with DG to the Q_{loss} without DG.

$$QLI = \frac{Q_{lw/DG}}{Q_{lw0/DG}} \times 100. \quad (9)$$

The lower the value of the index indicates the better in terms of reduction in reactive power loss with optimal location and capacity of DG.

Voltage deviation index (VDI): Improvement in voltage profile mainly dependent on the location and sizing pair of DG. This index penalizes the sizing and location pair that provides higher deviation from nominal voltage. The network performance is better when VDI is close to zero.

$$VDI = max\left(\frac{\left|\overline{V_1}\right| - \left|\overline{V}_{m\_DG}\right|}{\left|\overline{V_1}\right|}\right) \times 100 \mu m_{DG} \; is \; 2 \; to \; N_b. \quad (10)$$

DG Penetration ($\%P_{DG}$): It is defined as the ratio of total power injected by DG into the system to the summation of total power injected by DG and power injected by the system.

$$\%P_{DG} = \frac{\mathrm{P_{wDG}}}{\mathrm{P_{wDG}} + \mathrm{P_{woDG}}} \times 100. \quad (11)$$

Percentage power loss reduction ($\%P_{ls}$): It is defined as the ratio of difference in power losses of without and with DG to the power losses without DG in the system. Higher in reduction percentage indicates the maximum reduction in power losses.

$$\%P_{ls} = \frac{P_{lswoDG - P_{lswDG}}}{P_{lsw0DG}} \times 100 \quad (12)$$

2.5 Multi objective function

Optimal location and capacity of DG is a non linear, non differentiable combinatorial optimization problem. In this study, a quantum inspired evolutionary algorithm has been used to find the location and capacity of DG. The effectiveness of the proposed algorithm is tested with a multi objective function which includes real power loss, reactive power loss, total power injected by DG and voltage deviation index. Mathematical problem formulation of multi objective function is given as follows.

$$min(MOF) = (\propto_1 \times P_{loss} + \propto_2 \times Q_{loss} + \propto_3 \times VDI + \propto_4 \times P_{wDG}) \quad (13)$$

where $\propto_1 + \propto_2 + \propto_3 + \propto_4 = 1$

The weight values for this typical operation are considered as follows. In the analysis, real power losses and reactive power losses are considered as most important weights with factors 0.5 and 0.3. The third and fourth significant weights are voltage deviation index and power injected by DG with values 0.15 and 0.05.

3 Algorithm

In 90's many research efforts have been made in the field of quantum computing. Quantum computers which work on the principles of quantum mechanics can offer more processing power to solve some engineering optimization problems as compared with classical computers. In quantum mechanics, superposition principle states that a particle can be simultaneously in two different states, which offers high degree of parallelism. Shor's algorithm [37] shown the superiority for factoring the large numbers, the prime factor of a n-digit number can be found with Shor's algorithm in polynomial time whereas the well known classical algorithms have complexity of $O\left(2^{n^{\frac{1}{3}}} \log(n)^{\frac{1}{3}}\right)$. Grover's algorithms [38] also shown its superiority for searching the database, the complexity of Grover's algorithm for searching an item in an non ordered database with n-items is $O(\sqrt{n})$ whereas the classical algorithms have complexity of $O(n)$.

The researches on integration of quantum computing and evolutionary algorithms are developed in 90's. Two different categories are created, first one focuses mainly on drawbacks of quantum algorithms and the other focuses on developing new algorithms which are inspired from principles of quantum mechanics i.e., quantum inspired evolutionary algorithms [39]. In later approaches these algorithms are executed on classical computers.

Quantum computation is generally defined as the study of managing information using quantum mechanical system. Narayanan and Moore [40] have proposed a quantum optimization algorithm by incorporating some concepts and principles quantum mechanics into quantum computation i.e., interference crossover into genetic algorithm. Han and Kim [39] initially proposed quantum inspired evolutionary algorithms, Q-gates are used for convergence. Like evolutionary algorithms, QiEAs are also characterized by the use of a fitness evaluation mechanism, population diversity and representation of individuals. The algorithm is inspired by merging some concepts and principles of quantum computing with evolutionary algorithms to optimize some engineering optimization problems on classical computer. The major difference between QiEA and classical evolutionary algorithm is the basic unit to store the information. In classic evolutionary algorithm, binary digits are mainly used to store the information in one of the two states either '1' or '0'. In case of QiEA, quantum bit or Q-bit is used to store the information in superposition of two states.

Quantum inspired evolutionary algorithms are mainly rely on concept of quantum mechanics i.e., "quantum bit", in short known as Q-bit viz., smallest unit of information and superposition of states [34].The state of Q-bit can be represented as follows:

$$|\varepsilon\rangle = \varnothing|a\rangle + \delta|b\rangle, \tag{14}$$

where $\varnothing \& \delta$ are complex numbers, which represents the probability amplitudes of the corresponding states. $|\varnothing|^2 \& |\delta|^2$ shows the probability of quantum bit to be in state '0' or in state '1'. The normalization of amplitudes can be represented as

$$|\varnothing|^2 + |\delta|^2 = 1. \tag{15}$$

QiEA with binary representation can perform well on engineering optimization problems where this kind of representation is suited the most. Each individual in the Q-bit can be represented as $q_i = \left[\varnothing_i \delta_i\right]^T$. The population of Q-bit individuals are represented as $Q(t) = \left\{q_1^t, q_2^t, \dots q_n^t\right\}$ where t represents the generation with n-population size. The individual Q-bit at t generation with m population size is defined as

$$q_i^t = \left[\begin{array}{c|c|c|c} \varnothing_1^t & \varnothing_2^t & \dots & \varnothing_m^t \\ \delta_1^t & \delta_2^t & & \delta_m^t \end{array} \right]. \tag{16}$$

Over a past few decades, many researchers have used QiEA to study different optimization problems. However, some pending issues are to be studied in QiEA. QiEA uses simple probabilistic model and unable to represent high order relationship between variables. Secondly, QiEA is unable to deal with multi model landscape problems, especially symmetric optimization problems. In QiEA, information between the individuals can be shared by migration method which makes all the individuals converge to the same solution.

Adaptive quantum inspired evolutionary algorithm (AQiEA) is used to overcome some of the limitation in QiEA. In AQiEA, two Q-bits are used in population whereas QiEA uses a single Q-bit to store the information. The first Q-bit in AQiEA is used to store the solution vector variables and the second Q-bit is used to scale and rank the solution vector. The operation of quantum computers is mainly dependent uses Q-bits. The information of Q-bit can be in both states due to the superposition. Quantum particles which are in superposition of states can be entangled with one another. In quantum systems, parallel computation can be performed with the use of these entangled particles. Quantum computation is mainly dependent on three axioms: superposition axiom generally gives the information of Q-bit in the possible states of a given quantum system. Measurement axiom gives the relevant information about the states of Q-bit that we can access and the evolution of state of quantum system with respect to time is generally given by Unitary Evolution axiom. AQiEA uses some principles of quantum mechanics such as superposition, measurement and entanglement.

The solution string of a quantum system can be generated from Q-bit string (σ) where $\sigma\varepsilon(\varnothing, \delta)$ by using a measurement operator. In quantum system, the collapse of superposition of states can be observed by the application of measurement operator and in case of classical computers collapse doesn't occur naturally. A new string (N_{qs}) which is of same length of Q-bit string is generated. The values in N_{qs} is varied between 0 and 1. A new measured value string (N_{ms}) is generated after measurement operation on Q-bit string. The length of N_{ms} is same as the length of Q-bit string. The measured value in N_{ms} is obtained by comparing the generated random number at N_{qs} to square of $\varnothing$. At t generation the expression is normally given as follows:

$$N_{qs}(t) < \varnothing^2(t)\begin{cases} N_{ms}(t) = \varnothing^2(t) \\ otherwise N_{ms}(t) = \delta^2(t). \end{cases} \tag{17}$$

Tabulated results in Table 2 shows the detailed analysis of measurement operator with different Q-bits.

Entanglement is generally defined as two or more Q-bits which are entangled with others and separated by a distance. Any operation performed on one of the Q-bit would affect the sate of other Q-bit. The equation is given as follows

$$\left|\varepsilon_{2k}(t)\right\rangle = f_1(\left|\varepsilon_{1k}(t)\right\rangle) \tag{18}$$

In this study, an adaptive quantum based crossover operator is used a variation operator and is given as follows:

$$\left|\varepsilon_{1k}(t+1)\right\rangle = f_2\left(\left|\varepsilon_{2k}(t)\right\rangle, \left|\varepsilon_{21}(t)\right\rangle, \left|\varepsilon_{1k}(t)\right\rangle, \left|\varepsilon_{11}(t)\right\rangle\right)$$

Two Q-bits are entangled with each other, the amplitude of second Q-bit is determined by influence of first Q-bit value. Second Q-bit influences the first Q-bit by adaptive quantum rotation crossover operator. Quantum registers are used to represent the solution vector of a specified problem with number of variables and used to store Q-bits. The worst and best fittest solution vectors in the second Q-bit are considered as value 0 and 1. The remaining solution vectors in the second Q-bit are given scaled ranks between 1 to 0. If p represents the total population used to determine the fitness function with x variables.

$$\begin{bmatrix} QR_1 \\ \vdots \\ \vdots \\ QR_p \end{bmatrix} = \begin{bmatrix} D_{11} & \cdots & \cdots & D_{1x} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ D_{p1} & \cdots & \cdots & D_{px} \end{bmatrix} \tag{19}$$

Table 2 Measured operator on Q-bit string

t	1	2	3	4	…	N_p
$\varnothing^2(t)$	0.82	0.61	0.34	0.29	…	0.71
$\delta^2(t)$	0.18	0.39	0.66	0.71	…	0.29
$N_{qs}(t)$	0.34	0.92	0.65	0.84	…	0.26
$N_{ms}(t)$	0.82	0.39	0.66	0.71	…	0.71

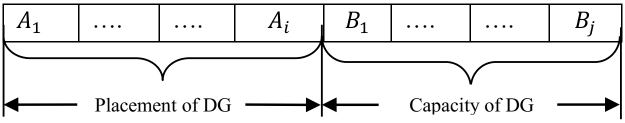


Fig. 1 Chromosome representation of AQiEA With DG

The main objective of the study is to reduce the power losses in the distribution network with implementation of DG. The solution vector for optimization problem is given as follows

$$Q_{DG} = \begin{bmatrix} DG_{P1}^{1} & \cdots & DG_{Pi}^{1} & DG_{C1}^{1} & \cdots & DG_{Cj}^{1} \\ DG_{P1}^{2} & \cdots & DG_{Pi}^{2} & DG_{C1}^{2} & \cdots & DG_{Cj}^{2} \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ DG_{P1}^{p-1} & \ldots & DG_{Pi}^{p-1} & DG_{C1}^{p-1} & \cdots & DG_{Cj}^{p-1} \\ DG_{P1}^{p} & \cdots & DG_{Pi}^{p} & DG_{C1}^{p} & \cdots & DG_{Cj}^{p} \end{bmatrix}, \quad (20)$$

where p represents the total population used in the system and *i&j* represents total number of variables used in the system for location of DG, size of DG and open switch. $\mathrm{DG}_{\mathrm{Pi}}^{\mathrm{p}}$ represents the placement of DG at *i*th variable with p population. $\mathrm{DG}_{\mathrm{Cj}}^{\mathrm{p}}$ represents the capacity of DG at *j*th variable with p population.

Optimal location and capacity of DG are two key important factors to reduce the power losses and optimization of DG in distribution network is a difficult non-linear combinatorial optimization problem which involves continuous (optimal sizing of DG) and discrete variables (optimal location of DG). Optimal size of DG is varied from $\mathrm{P}_{\mathrm{DG}}^{\mathrm{min}}and\mathrm{P}_{\mathrm{DG}}^{\mathrm{max}}$. Optimal location of DG is varied from 1 to $\mathrm{N_b}$. Quantum chromosome representation for implementation of DG is shown in Fig. 1.

In evolutionary algorithms, symbol, binary or numeric values are used to represent the chromosome. In case of QiEA, the chromosome representation is mainly dependent on Q-bit representation. QiEA doesn't need any operators to maintain the diversity in the population. The population diversity in QiEA can be maintained by using quantum gates or Q-gates. In AQiEA, instead of Q-gates, rotation strategies are mainly applied to maintain the population diversity.

The proposed algorithm has applied different rotation strategies (three) to converge the population towards global optima.

Rotation towards the Best Strategy (R-I): Individuals in the population are rotated towards the best individual. It is sequentially implemented for each solution vector except the best solution vector.

Rotation away from the Worse Strategy (R-II): It is primarily used for exploitation purpose. Best individual in the population is moved away from the worse. As it is rotated away from worse the search take place in all dimensions.

Rotation towards the Better Strategy (R-III): It is primarily used for exploration purpose. Two individuals are randomly selected in the population and the inferior one is rotated towards the best individual.

The pseudo code of the proposed algorithm is shown below:

3.1 Pseudo code

Initialization

N_{Qb}=Number of Quantum Registers (QR_1)

for i=1: N_{Qb} *{*

QR_1 (i) =random (0, 1) ;}

Do {

Formation of Measurement Operator (Q_m)

for i=1: N_{Qb} *{*

if random(0,1)<$(QR_1(i))^2$

varb (k)= $(QR_1(i))^2$

else

varb (i)= $(1-(QR_1(i))^2)$}

Computing Fitness Calculation

for i=1:N_{Qb}{

fitness_function=DLF(varb(i))}

Assign Quantum registers QR_2 using solution vector of Quantum registers QR_1

Apply Different Rotation Strategies (Adaptive Quantum based crossover operator) (QR_{1c})

Elitist selection between QR_{1c} and QR_1

} While (!termination_criteria)

3.2 Description

1. All parameter are initialized such as population size, maximum number of iterations, etc. Quantum inspired register QR_1 is initialized with respect to number of variables.
2. Solution string is generated by using measurement operator from Q-bit string. Initially, a random number is generated between [0 1]. If the random number is

less than the square of QR_1, the square of QR_1 is selected else one minus square of QR_1 is selected.

3. In order to compute the fitness of each solution vector a direct load flow study is used.The main objective of the study is to reduce the power losses by implementing DG in distribution network.
4. Quantum register QR_2 stores the scaled and ranked objective function value of corresponding solution vector.
5. The proposed algorithm has applied different rotation strategies (three) to converge the population towards global optima.
6. The fittest one in the population is moved to the next generation as per Darwinian principle. Each individual in the population will compete with the other and the best will move to the next generation. In the study, tournament selection is generally applied to find the best individual in the population.
7. Termination criterion is executed based on maximum number of iterations.

4 Results and discussion

The effectiveness of the proposed algorithm is tested on IEEE benchmark test bus systems with an objective to reduce the power losses by implementing DG with ZIP load models. The proposed method is coded in Matlab software which is installed in an Intel® Core™ i-3 processor having 1.80 GHz speed with a set up memory of 4 GB. Two different cases are created to test the effectiveness of AQiEA. First case represents the independent implementation of DG on different ZIP load models. Ten different scenarios are used to test the effect of DG on seven different ZIP load models. Performance indices are also considered in the study. The second case is used, to test the performance of the proposed algorithm with different ZIP load models. Two benchmark test bus systems (33 bus system & 69 bus system) are used to test the performance of AQiEA. Results obtained with AQiEA are compared with other methods such as PSO, SOS, JO, ALO and DFO. Table 3, shows the initial data for both test bus system which includes total real load, reactive load, real power

Table 3 Initial load data for both test bus systems

Particular	Value (33 Bus system)	Value (69 Bus system)
Total active power demand (MW)	3.715	3.8100
Total reactive power demand (MVAr)	2.3000	2.6940
Buses	1 to 33	1 to 69
Sectionalizing switches	1 to 32	1 to 68
Maximum power rating of DG (MW)	1	1
Active power loss (kW)	202.6200	224.9400
Reactive power loss (kVAr)	135.2300	102.1200
Minimum voltage (p.u)	0.9132	0.9092

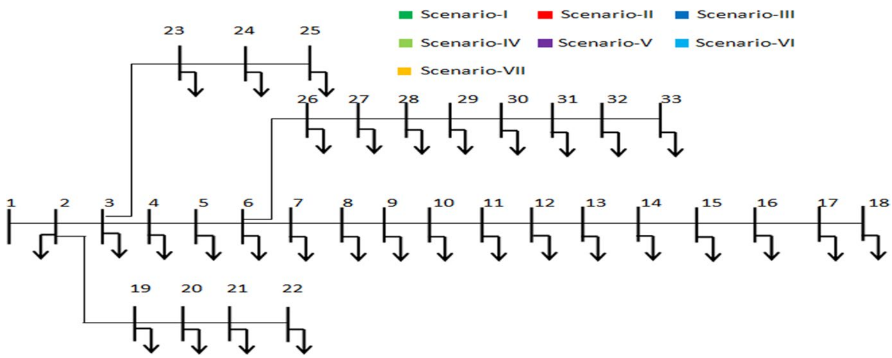


Fig. 2 Single line diagram of first test bus system

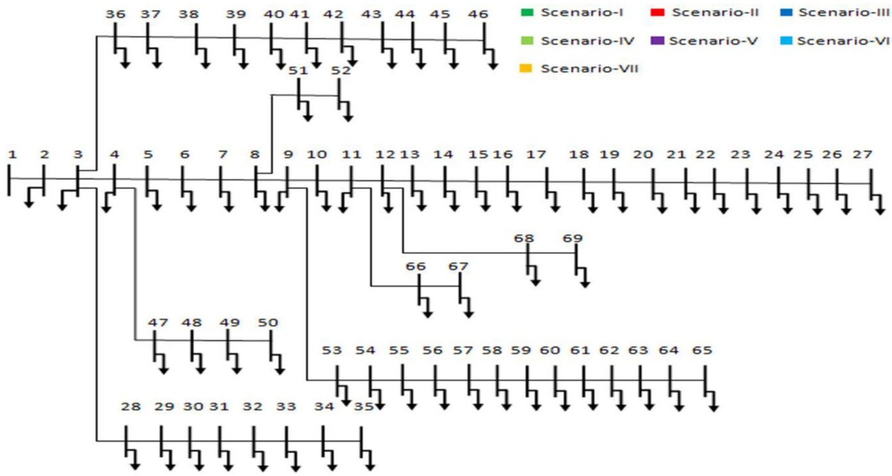


Fig. 3 Single line diagram of second test bus system

losses, reactive power losses, minimum voltage etc. Figures 2 and 3 shows the single line diagram representation of both test bus systems. In Case A, seven different load models are used with ten different scenarios, last three scenarios represents the practical ZIP load model which is combination of all seven load models. From Figs. 2 and 3, it has been observed that seven different scenarios are used. Whereas, in both figures the load acted on the bus is shown with black color which represents constant power load model.

DGs are mainly used in distribution network to reduce the power losses. Optimal location and capacity plays an important role to reduce the power losses. Improper location and capacity of DG induces high power losses and poor voltage regulation in the system. Some constraints and assumptions are considered.

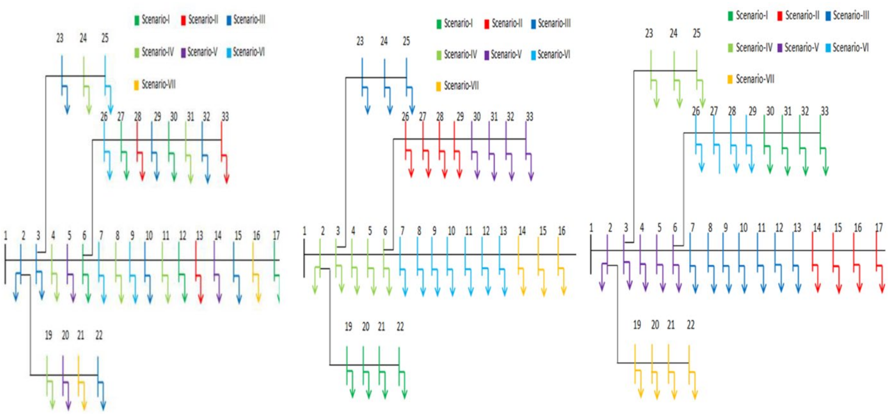
4.1 Constraints and assumptions

1. All nodes in the network are considered as candidate nodes for optimal allocation and size of DG.
2. Substation bus or reference bus voltage is 1.0 p.u.
3. Only one DG is allowed in each bus. Repetition of bus numbers are not allowed for location of DG.
4. Maximum allowable size of DG is limited to 1.0 MW.
5. System operating with voltages S_{base}=100 MVA and V_{base}=12.66 kV.
6. The parameters of AQiEA are N_{pop}=50, $Iter_{Max}$=100, $Con = 0.0001$.
7. Maximum and minimum allowable voltages in the network are 1.05 p.u. and 0.95p.u.

4.2 Case-A

Minimization of power losses in distribution network is one of the main concerns for distribution utilities. Implementing DGs into distribution network is considered as an alternative technique to reduce the power losses. Some researchers have studied this important optimization problem with fixed load model which doesn't vary with time. The load at distribution network is not fixed and changing from time to time and majority of loads are mainly dependent on ZIP loads. In this study, seven different load models are considered to study the effect of DGs. Ten different scenarios are created with seven different load models, first seven scenarios are independent implementation of ZIP load models i.e., a single ZIP load model is implemented on test bus system. In Scenario-I, the total load acted on the system is Air Conditioner, for every individual bus the load is considered as Air Conditioner. Similarly for other Scenarios, the total load acted on the system is Incandescent lamp, LED light, Microwave, Vacuum cleaner, PC & Refrigerator. Scenarios VIII, IX and X has combination of all ZIP load models. In Scenario-VIII random loads are initialized at every bus, whereas in case of Scenario-IX and X loads are assigned with respect to lateral and sub-laterals. Figure 4 represents the load acted on the first test bus system for Scenario VIII–X. Similarly, Figs. 5, 6, and 7 represents the load acted on the second test bus system for Scenario VIII–X. The total load acted on the system for different scenarios are given below.

Scenario I: Air conditioner
Scenario II: Incandescent lamp
Scenario III: LED light
Scenario IV: Microwave
Scenario V: Vacuum cleaner
Scenario VI: PC (Monitor and CPU)
Scenario VII: Refrigerator
Scenario VIII: Combination of all loads from Scenario-I to Scenario-VII
Scenario IX: Combination of all loads from Scenario-I to Scenario-VII
Scenario X: Combination of all loads from Scenario-I to Scenario-VII



(a) Single line diagram of first test bus system for Scenario VIII

(b) Single line diagram of first test bus system for Scenario IX

(c) Single line diagram of first test bus system for Scenario X

Fig. 4 Single line diagram of firsttest bus system for Scenario VIII, IX and X

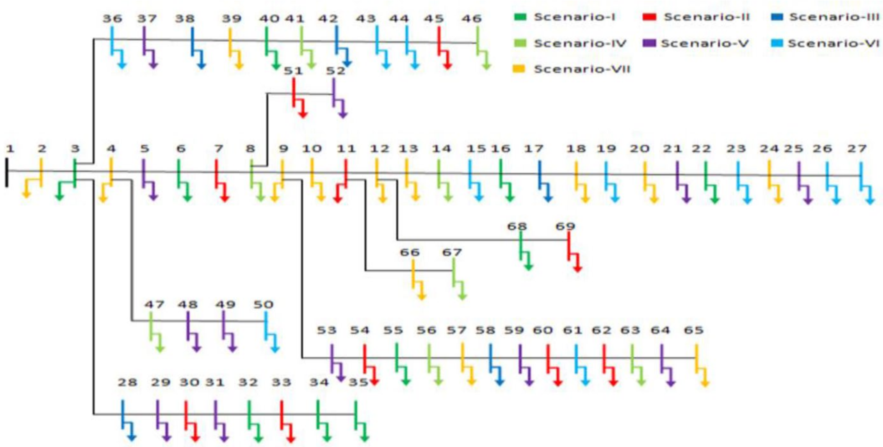


Fig. 5 Single line diagram of second test bus system for Scenario VIII

4.2.1 33 bus system

The effect of DG on ZIP load models are tested with different scenarios. Table 4 shows the comparative analysis of different scenarios with performance indices. It has been observed that power losses are reduced in every scenario by placing DG at

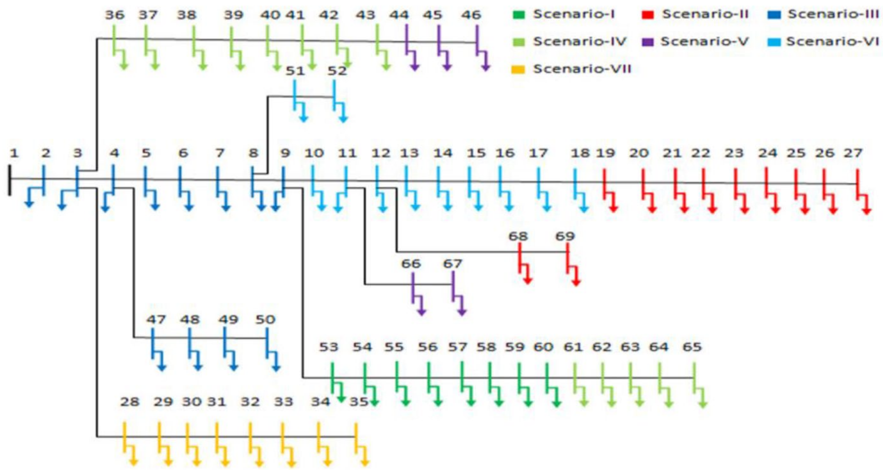


Fig. 6 Single line diagram of second test bus system for Scenario IX

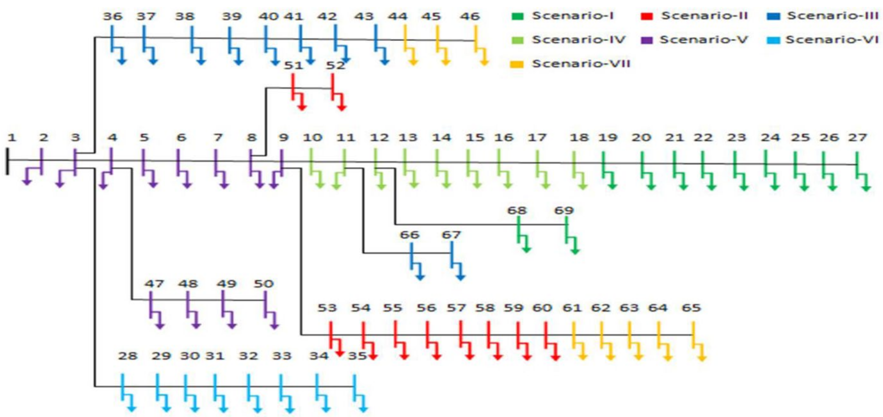


Fig. 7 Single line diagram of second test bus system for Scenario X

optimal location with optimal size. Multiple DGs are used for the study to reduce the power losses. Scenario I to VII represents the independent implementation of seven different ZIP load models. Scenario VIII to X represents the combination of all ZIP load models. Total active power losses induced in the system before implementation of DG for different scenarios from scenario I to III are 169.57 kW, 162.6216 kW and 140.8218 kW. Reactive power losses induced in the system without DG are 112.85 kVAr, 108.11 kVAr and 93.39 kVAr. Similarly, the active and reactive power losses induced in the system for scenarios IV–X are shown in the Table 4. After implementing DG in the system for different scenarios, reduction in power loss is observed. Total active and reactive power losses reduced for scenario I–III are 49.17 kW, 59.117 kW, 49.0517 kW and 34.16 kVAr, 40.73 kVAr, 33.81 kVAr.

Table 4 Comparative analysis of different scenarios with performance indices on ZIP load models for first test bus system

	Scenario-I	Scenario-II	Scenario-III	Scenario-IV	Scenario-V	Scenario-VI	Scenario-VII	Scenario-VIII	Scenario-IX	Scenario-X
Location	30	30	13	14	14	24	24	24	24	24
	24	14	30	30	24	30	30	13	13	14
	14	24	24	24	30	13	13	30	30	30
Size (MW)	1.0000	0.9531	0.6534	0.7233	0.6319	1.0000	1.0000	1.0000	1.0000	1.0000
	1.0000	0.6709	0.8792	1.0000	1.0000	1.0000	0.9000	0.7019	0.7239	0.6591
	0.7407	1.0000	1.0000	1.0000	0.9067	0.8	0.6671	0.9644	0.9243	1.0000
P_{lswoDG} (kW)	169.5719	162.6216	140.8219	174.0411	149.7896	195.7762	151.2042	159.5579	162.7983	160.4977
P_{lswDG} (kW)	49.1719	59.117	49.0517	56.5965	55.7679	67.5015	55.5359	52.4436	57.956	51.4428
Q_{lswoDG} (kVAr)	112.8575	108.1123	93.3913	115.8322	99.4950	130.5479	100.4015	105.9147	108.3489	106.5449
Q_{lswDG} (kVAr)	34.1648	40.7335	33.8088	39.136	38.3832	46.5533	38.2201	36.1975	39.9828	35.5071
$RPLI_{woDG}$ (%)	100	100	100	100	100	100	100	100	100	100
$RPLI_{wDG}$ (%)	28.9978	36.3527	34.8326	32.5192	37.231	34.4792	36.7292	32.8682	35.6001	32.0522
$RePLI_{woDG}$ (%)	100	100	100	100	100	100	100	100	100	100
$RePLI_{wDG}$ (%)	30.2725	37.6770	36.2012	33.7868	38.5780	35.6601	38.0673	34.1761	36.9019	33.3265
VDI_{woDG} (%)	7.9400	7.7000	7.1200	8.0300	7.3600	8.5400	7.3900	7.6200	7.7900	7.6000
VDI_{wDG} (%)	2.6400	2.8100	2.5400	2.8100	2.7200	3.1800	2.7200	2.5900	2.7600	2.6600
P_{Load} (MW)	3.6305	3.4265	3.2966	3.5930	3.2962	3.6938	3.3351	3.5016	3.4512	3.4943
P_{DG} (MW)	2.7407	2.6240	2.5325	2.7233	2.5386	2.8000	2.5671	2.6662	2.6482	2.6591
$\%P_{DG}$ (%)	75.38	76.57	76.82	75.79	77.01	75.8	76.97	76.14	76.73	76.09
$\%P_{ls}$ (%)	71.0023	63.6475	65.1675	67.4809	62.7692	65.5211	63.2709	67.1319	64.4001	67.9479

Similarly, reduction in power loss is observed for every scenario. High reduction in power loss is observed in scenario I from 169.57 to 49.17 kW with percentage power loss reduction of 71%. Scenario X, IV and VIII are also having high reduction in power loss with percentage power loss reduction of 67.94%, 67.48% and 67.13%. Multiple DGs (three) are used to reduce the power losses, it has been observed that total penetration of DG in every scenario is above 75%. The total real power injected by DG in every scenario is above 2.5 MW. It has been observed from results that optimal location of DG is similar for scenario I, II, IV, V and X. The optimal locations for these scenarios are 30, 24 and 14. The remaining scenarios such as scenario III, VI, VII, VIII and IX are also having same optimal location 30, 13 and 24. The optimal locations of DG for all scenarios are similar, which is mainly due to the linear change in load. The optimal sizing of DG is changing for every scenario. Performance indices of DG for every scenario are also included in the study. Real power loss index, reactive power loss index and voltage deviation index are included. Scenario V, VII, II and IX has high real and reactive power loss index. Whereas, scenario I and X has low real and reactive power loss index. Real power loss index for scenario V, VII, II and IX are 37.23%, 36.72%, 36.35% and 35.6%. Reactive power loss index for scenario V, VII, II and IX are 38.57%, 38.06%, 37.67% and 36.91%. Figure 8 shows the voltage profile improvement for all scenarios on first test bus system. Figure 9a shows the power losses induced in the system for every scenario before and after implementation of DG. Figure 9b shows the power loss index both real and reactive in the system for every scenario after implementation of DG. Figure 9c shows the voltage deviation index for every scenario before and after implementation of DG.

4.2.2 69 Bus system

The performance of the proposed algorithm with DG is tested on second test bus system. Similar to first test bus system, it is also considered seven different ZIP load models with ten different scenarios. Table 5 shows the comparative analysis of different scenarios with performance indices. The total real power losses induced in the system without DG are 183.89 kW, 171.49 kW and 144.72 kW for scenario I, II and III. Similarly, the total reactive power losses induced in the system without DG are 84.35 kVAr, 79.04 kVAr and 65.34 kVAr for scenario I, II and III. After implementing DG in the system for different scenarios, reduction in power loss is observed. Total active and reactive power losses reduced for scenario I–III are 45.45 kW, 57.01 kW, 46.24 kW and 24.53 kVAr, 29.44 kVAr, 24.7 kVAr. Similarly, reduction in power loss is observed for every scenario. High reduction in power loss is observed in scenario I from 183.89 to 45.46 kW with percentage power loss reduction of 75.28%. Scenario IV, IX and VII are also having high reduction in power loss with percentage power loss reduction of 71.25%, 71.22% and 68.89%. It has been observed that total penetration of DG in every scenario is around 60%. The total real power injected by DG in every scenario is above 2.0 MW. It has been observed from results that optimal location of DG is similar for scenario I, VI with location 60, 15, 61 and optimal location of DG is similar for scenario II, IV, VIII with location 60, 16, 61. The remaining scenarios have different optimal location i.e., scenarios III,

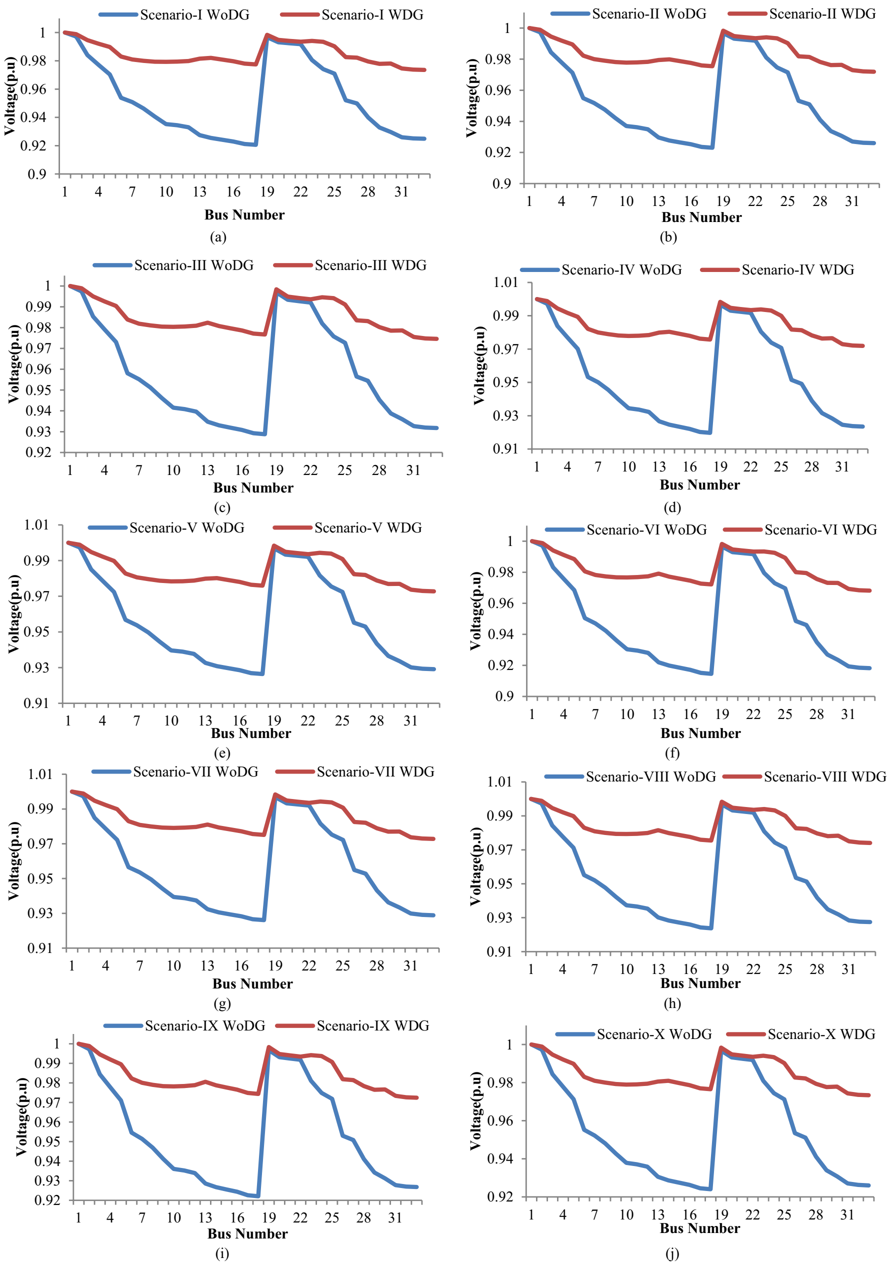
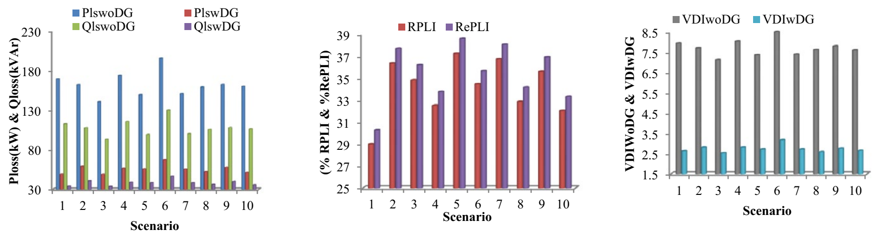


Fig. 8 Voltage profile improvement for all Scenarios on first test bus system

V, VII, IX and X have different locations. Scenario V, VII, X and II has high real and reactive power loss index. Whereas, scenario I has low real and reactive power loss index. Real power loss index for scenario V, VII, X and II are 34.28%, 33.85%,



(a) Real and reactive power losses before and after implementation of DG for first test bus system

(b) Real and reactive power loss index after implementation of DG for first test bus system

(c) Voltage Deviation index for first test bus system

Fig. 9 Real and reactive power losses and performance indices of first test bus before and after implementation of DG

33.34% and 33.24%. Reactive power loss index for scenario V, VII, X and II are 38.41%, 38.12%, 37.45% and 37.24%. Figure 10a shows the power losses induced in the system for every scenario before and after implementation of DG. Figure 10b shows the power loss index both real and reactive in the system for every scenario after implementation of DG. Figure 10c shows the voltage deviation index for every scenario before and after implementation of DG. Figure 11 shows the voltage profile improvement for all scenarios on Second test bus system.

4.3 Case-B

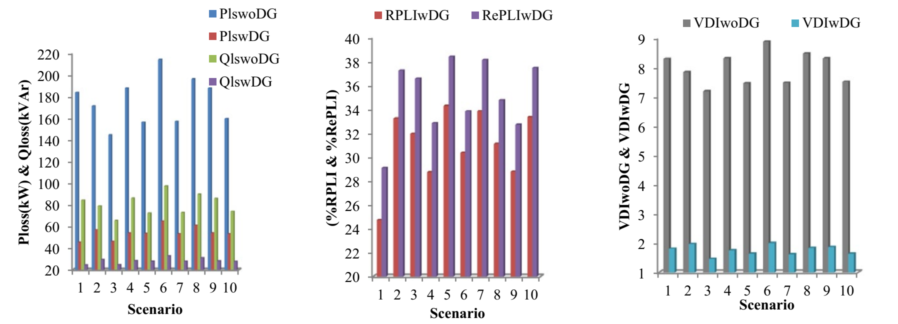
The efficacy of the proposed algorithm (AQiEA) as compared with other 'state of Art techniques' is tested on two benchmark test bus systems. AQiEA is relatively new and powerful intelligent evolutionary technique used for solving many engineering optimization problems. AQiEA uses probabilistic representation with Q-bits. Three different scenarios which is combination of all seven ZIP loads are considered to test the effectiveness of proposed algorithm. Optimal location and capacity of DG not only reduces the power losses but also improves the voltage profile of the system. In this study, a multi objective function is considered, combination of power losses both real and reactive, voltage deviation index and power injected by DG.

4.3.1 33 Bus system

Total real and reactive power losses in the system after implementing DG with proposed algorithm for scenario VIII are 52.44 kW and 36.19 kVAr with optimal location 24, 13, 30 and capacity 1 MW, 701 kW, 965 kW respectively. Total real power losses, reactive power losses, power injected by DG, multi objective function value and percentage power loss reduction values for proposed algorithm and other state of art techniques are shown in Table 6. PSO, SOS, JO, ALO and DFO have active power loss of 63.08 kW, 65.29 kW, 62.97 kW, 59.22 kW and 56.41 kW. The total power injected by DG into system for AQiEA is 2.67 MW. In comparison with AQiEA other algorithms have high injection of powers into the system. It has been observed from tabulated results that AQiEA has high

Table 5 Comparative analysis of different scenarios with performance indices on ZIP load models for second test bus system

	Scenario-I	Scenario-II	Scenario-III	Scenario-IV	Scenario-V	Scenario-VI	Scenario-VII	Scenario-VIII	Scenario-IX	Scenario-X
Location	60	16	63	16	63	15	60	60	60	60
	15	61	60	61	17	61	16	16	17	63
	61	60	15	60	60	60	63	61	61	15
Size (MW)	0.9998	0.5237	0.4230	0.5013	0.4346	0.5228	1.0000	1.0000	0.9871	0.9852
	0.5346	0.5017	0.9879	0.7261	0.5130	0.7506	0.4831	0.4844	0.5383	0.4600
	0.6491	0.9950	0.5543	0.9553	1.0000	1.0000	0.4511	0.6983	0.6542	0.5350
P_{lswoDG} (kW)	183.8980	171.4910	144.7287	187.8056	156.3543	214.3218	157.2478	196.4364	187.8365	159.5791
P_{lswDG} (kW)	45.4564	57.0091	46.2496	53.9789	53.6033	65.0632	53.2283	61.0972	54.0576	53.2114
Q_{lswoDG} (kVAr)	84.3562	79.0466	65.5407	86.1551	72.3990	97.4177	72.9241	89.5877	85.9815	73.8355
Q_{lswDG} (kVAr)	24.5318	29.4407	24.7011	28.2889	27.8098	32.9679	27.8036	31.1360	28.1317	27.6550
$RPLI_{woDG}$ (%)	100	100	100	100	100	100	100	100	100	100
$RPLI_{wDG}$ (%)	24.7183	33.2432	31.9561	28.7419	34.2832	30.3577	33.8500	31.1028	28.7791	33.3449
$RePLI_{woDG}$ (%)	100	100	100	100	100	100	100	100	100	100
$RePLI_{wDG}$ (%)	29.0812	37.2447	36.5722	32.8349	38.4114	33.8418	38.1268	34.7568	32.7183	37.4549
VDI_{woDG} (%)	8.2900	7.8400	7.1800	8.3100	7.4500	8.8800	7.4700	8.4700	8.3100	7.5100
VDI_{wDG} (%)	1.8100	1.9700	1.4600	1.7500	1.6400	2.0000	1.6200	1.8400	1.8700	1.6400
P_{Load} (MW)	3.7290	3.5190	3.3900	3.6831	3.3881	3.7842	3.4295	3.6484	3.6697	3.4566
P_{DG} (MW)	2.1836	2.0506	1.9654	2.1828	1.9477	2.2736	1.9342	2.1828	2.1796	1.9802
$\%P_{DG}$ (%)	58.56	57.42	57.97	59.27	57.49	60.08	56.39	59.83	59.39	57.29
$\%P_{ls}$ (%)	75.2817	66.7568	68.0439	71.2581	65.7168	69.6423	66.1501	68.8972	71.2209	66.6552



(a) Real and reactive power losses before and after implementation of DG for second test bus system

(b) Real and reactive power loss index after implementation of DG for second test bus system

(c) Voltage Deviation index for second test bus system

Fig. 10 Real and reactive power losses and performance indices of second test bus before and after implementation of DG

reduction in power loss and minimum multi objective function. The proposed algorithm has minimum value of 37.25. SOS has maximum value of 46.72, followed by PSO of 45.34, followed by JO of 44.72, followed by ALO of 42.5, followed by DFO of 40.15. AQiEA has high percentage power loss reduction as compare with PSO, SOS, JO, ALO & DFO. Similarly for scenario IX and X, the real and reactive power losses in the system after DG installation with AQiEA is 57.95 kW, 39.98 kVAr and 51.44 kW and 35.51 kVAr. The optimal location of DG for scenario IX is same as scenario VIII. Scenario X has optimal location of 24, 14 and 30. The optimal size of DG for scenario IX and X are 1 MW, 723 kW, 924 kW and 1 MW, 659 kW, 1 MW respectively. It has been observed from tabulated results that, AQiEA has minimum power loss, maximum percentage power loss reduction and minimum multi objective function. The total power injected by DG for three scenarios are low in comparison with other algorithms. The total power injected by DG for three scenarios are 2.67 MW, 2.65 MW and 2.66 MW respectively. Other algorithms which are available for comparison have high injection of powers. Figure 12a shows the real power losses in the system after implementation of DG with different algorithms. Figure 12b shows the reactive power losses in the system after implementation of DG with different algorithms. Figure 12c shows the multi objective function value for different algorithms. Figure 12d shows the percentage power loss reduction in the system with different algorithms after implementation of DG. Figure 13 shows the comparison of voltage profiles for different algorithms.

4.3.2 69 Bus system

Total power losses induced in the system after implementing DG with proposed algorithm for all scenarios are shown in Table 7. Scenario VIII has power loss of 61.09 kW and 31.13 kVAr with optimal location and capacity 60, 16, 61 and

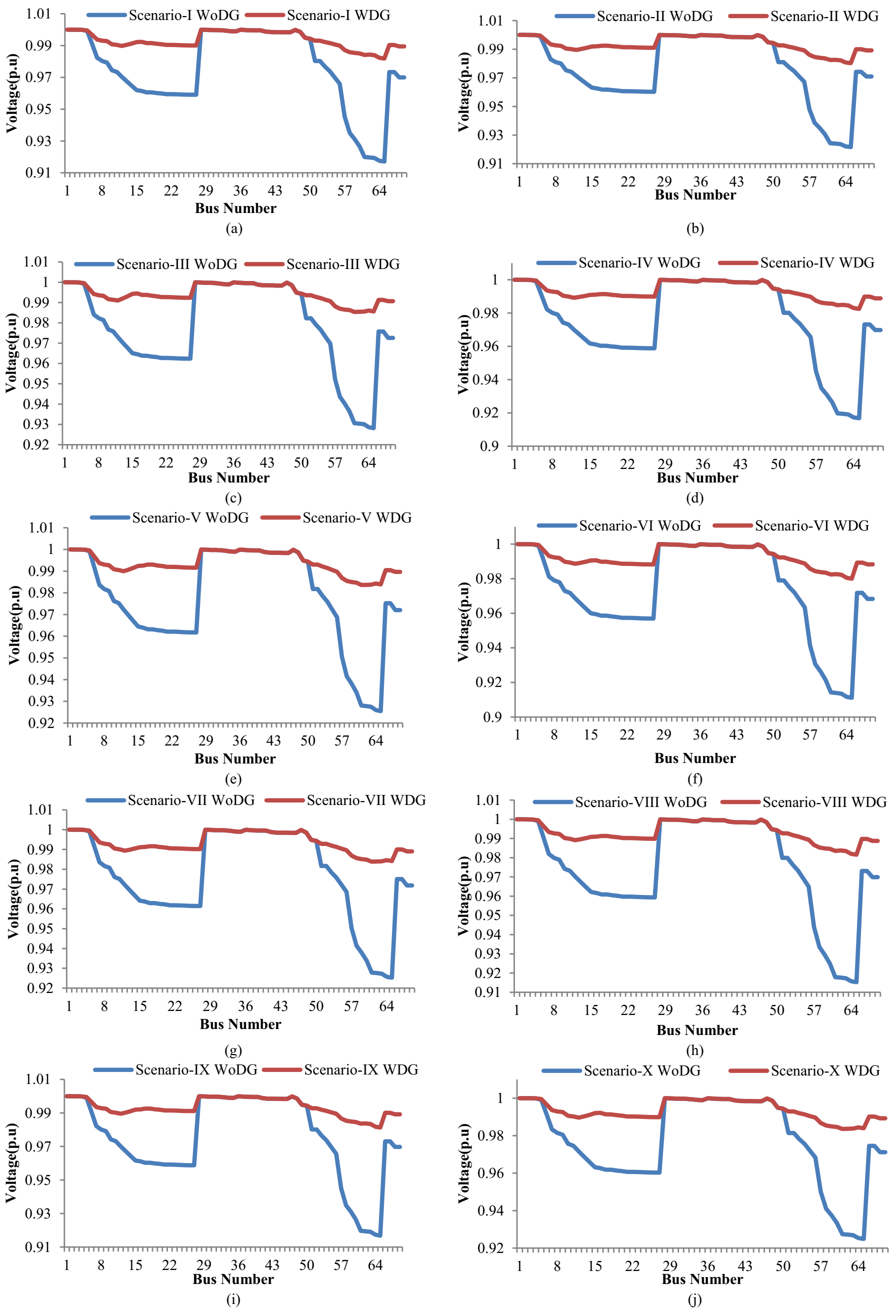
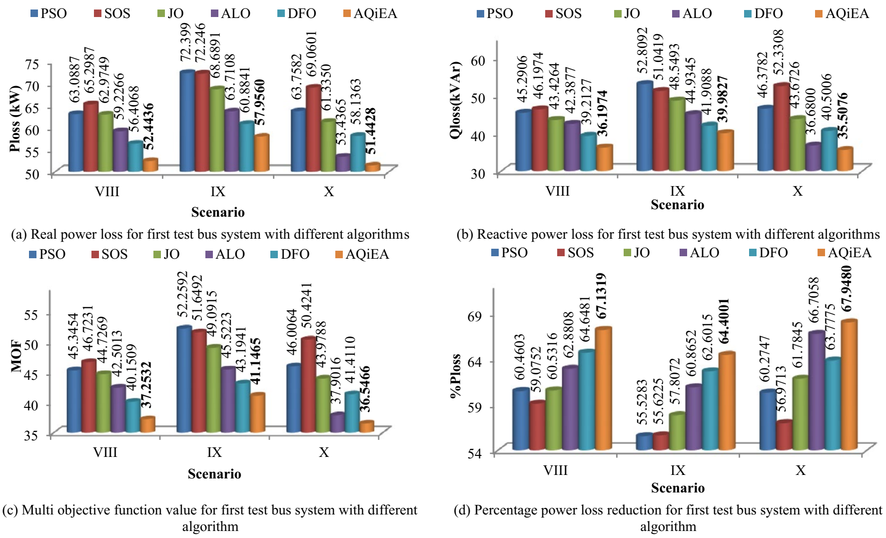


Fig. 11 Voltage profile improvement for all Scenarios on second test bus system

Table 6 Comparative analysis of AQiEA with state of art algorithms for first test bus system

		Loc			Sizing (MW)			P_{lswDG} (kW)	Q_{lswDG} (kVAr)	VDI_{wDG}	P_{DG} (MW)	MOF	$\%P_{ls}$ (%)
Scenario-VIII	PSO	26	25	30	1.0000	0.9872	1.0000	63.0887	45.2906	4.3000	2.9872	45.3454	60.4603
	SOS	24	29	27	1.0000	1.0000	1.0000	65.2987	46.1974	4.3000	3.0000	46.7231	59.0752
	JO	7	32	25	0.9799	1.0000	0.9884	62.9749	43.4264	4.2100	2.9683	44.7269	60.5316
	ALO	24	32	15	0.9783	0.9497	0.9152	59.2266	42.3877	1.9700	2.8432	42.5013	62.8808
	DFO	14	29	24	0.9429	0.9003	1.0000	56.4068	39.2127	2.7700	2.8432	40.1509	64.6481
	AQiEA	24	13	30	1.0000	0.7019	0.9644	**52.4436**	36.1974	2.5900	**2.6663**	**37.2532**	**67.1319**
Scenario-IX	PSO	26	32	24	0.9954	1.0000	1.0000	72.3992	52.8092	4.4736	2.9954	52.2592	55.5283
	SOS	5	24	13	1.0000	0.9439	0.9326	72.2458	51.0419	4.6603	2.8765	51.6492	55.6225
	JO	16	25	30	1.0000	1.0000	0.9194	68.6891	48.5493	2.4127	2.9194	49.0915	57.8072
	ALO	32	10	25	1.0000	0.9413	0.9734	63.7108	44.9345	2.7185	2.9147	45.5223	60.8652
	DFO	24	30	13	0.9693	0.9918	0.9536	60.8841	41.9088	2.2428	2.9147	43.1941	62.6015
	AQiEA	24	13	30	1.0000	0.7239	0.9243	**57.9560**	39.9827	2.7553	**2.6482**	**41.1465**	**64.4001**
Scenario-X	PSO	26	32	25	0.9998	1.0000	0.9959	63.7582	46.3782	4.2697	2.9957	46.0064	60.2747
	SOS	17	28	24	0.9589	1.0000	0.9943	69.0601	52.3308	3.1404	2.9532	50.4241	56.9713
	JO	26	24	29	1.0000	0.8987	1.0000	61.3350	43.6726	4.3022	2.8987	43.9788	61.7845
	ALO	24	30	11	0.9197	1.0000	0.9799	53.4365	36.6800	2.2958	2.8996	37.9016	66.7058
	DFO	31	9	23	0.9342	0.9668	0.9986	58.1363	40.5006	3.1761	2.8996	41.4110	63.7775
	AQiEA	24	14	30	1.0000	0.6591	1.0000	**51.4428**	35.5076	2.6622	**2.6591**	**36.5466**	**67.9480**

Bold indicates that AQiEA is performing better as compared with other algorithms in the table



(a) Real power loss for first test bus system with different algorithms

(b) Reactive power loss for first test bus system with different algorithms

(c) Multi objective function value for first test bus system with different algorithm

(d) Percentage power loss reduction for first test bus system with different algorithm

Fig. 12 Real and reactive power loss, Multi objective function value and percentage power loss reduction for first test bus system with different algorithms

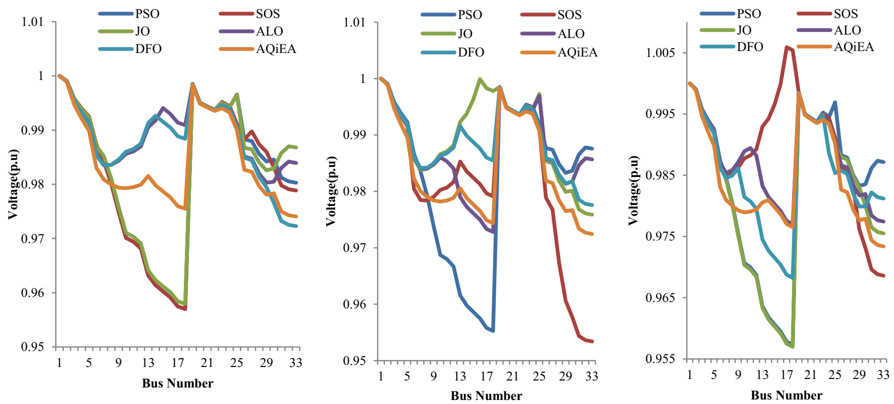


Fig. 13 Voltage profile improvement with different algorithms on first test bus system

1 MW 484 kW and 698 kW by AQiEA. The power losses with DG for PSO, SOS, JO, ALO and DFO are 79.12 kW, 77.63 kW, 71.24 kW, 68.71 kW and 67.28 kW respectively. It has been observed from tabulated results that proposed algorithm has minimum power loss as compared with state of art techniques. The power loss with proposed algorithm for scenario IX and X are 54.0575 kW, 28.1317 kVAr and 53.2112 kW, 27.6549 kVAr respectively. Whereas, power losses with DG by other algorithms used for comparison are 69.398 kW, 64.1165 kW, 71.163 kW, 61.2836 kW, 59.2654 kW and 54.0575 kW respectively. PSO and SOS has nearly equal amount of power loss for scenario X. The power losses with DG for scenario

Table 7 Comparative analysis of AQiEA with state of art algorithms for second test bus system

		Loc			Sizing (MW)			P_{lswDG} (kW)	Q_{lswDG} (kVAr)	VDI_{wDG}	P_{DG} (MW)	MOF	$\%P_{ls}$ (%)
Scenario-VIII	PSO	14	62	39	0.8431	1.0000	0.7917	79.1273	38.9036	4.0790	2.6348	51.4276	59.7185
	SOS	30	62	64	0.8829	0.6701	0.9432	77.6327	38.7733	3.0325	2.4962	50.6186	60.4794
	JO	52	58	61	0.7784	0.9137	0.9026	71.2400	34.5556	2.4792	2.5947	46.1536	63.7337
	ALO	68	62	60	0.9937	0.7142	0.9569	68.7094	33.7865	1.9584	2.6648	44.6533	65.0220
	DFO	14	63	64	0.7986	0.9481	0.7399	67.2760	33.6987	1.5154	2.4866	43.8947	65.7517
	AQiEA	60	16	61	1.0000	0.4844	0.6984	**61.0969**	31.1359	1.8417	**2.1828**	**40.0260**	**68.8973**
Scenario-IX	PSO	53	16	63	0.7649	0.8304	0.9486	69.3980	33.7054	3.5006	2.5438	44.9903	63.0540
	SOS	51	59	69	0.9847	0.7653	0.9371	64.1164	31.9027	2.4895	2.6870	41.8007	65.8658
	JO	68	57	65	0.9485	0.8113	0.8995	71.1629	34.9663	2.2340	2.6592	46.2378	62.1144
	ALO	68	61	60	0.9724	0.6896	0.9829	61.2836	30.6438	1.8785	2.6448	39.9953	67.3739
	DFO	62	22	58	0.9418	0.6644	0.8977	59.2653	29.8664	1.7901	2.5038	38.7446	68.4484
	AQiEA	61	18	62	0.9871	0.5383	0.6542	**54.0574**	28.1316	1.8699	**2.1795**	**35.6052**	**71.2210**
Scenario-X	PSO	41	18	63	0.9672	0.5438	1.0000	66.3235	36.9942	3.2841	2.51095	44.4348	58.4384
	SOS	30	61	59	0.8977	0.9428	0.7133	66.3271	33.1758	2.9345	2.5537	43.2880	58.4361
	JO	67	60	59	0.8432	0.6839	0.9318	63.1742	31.6981	1.9219	2.4588	41.2483	60.4119
	ALO	59	62	66	0.8789	0.9176	0.6427	59.7854	29.8516	2.0591	2.4391	39.0010	62.5355
	DFO	61	13	58	0.8486	0.8187	0.809	57.2292	28.9176	1.6084	2.4762	37.4378	64.1373
	AQiEA	61	64	16	0.9852	0.46	0.535	**53.2112**	27.6548	1.6404	**1.9801**	**35.0256**	**66.6552**

Bold indicates that AQiEA is performing better as compared with other algorithms in the table

X are 66.3272 kW for SOS, 66.3235 kW for PSO, 63.1742 for JO, 59.7854 kW for ALO and 57.2293 kW for DFO. In comparison with AQiEA other algorithms have high injection of powers into the system. It has been observed from tabulated results that AQiEA has high reduction in power loss and minimum multi objective function from all scenarios. The multi objective function for proposed algorithm for scenario VIII, IX and X is 40.026, 35.6053 and 35.0257. Scenario VIII, PSO has maximum value of 51.4277, followed by SOS of 50.6187, followed by JO of 46.1536, followed by ALO of 44.6533, followed by DFO of 43.8947. Similarly, for scenario IX and X, PSO has maximum value of 44.9903 and 44.4349, followed by SOS of 41.8008 and 43.288, followed by JO of 46.2379 and 41.2483, followed by ALO of 39.9954 and 39.0011, followed by DFO of 38.7447 and 37.4379. The total power injected by DG for three scenarios are low in comparison with other algorithms. The total power injected by DG for three scenarios are 2.1828 MW, 2.1796 MW and 1.9802 MW respectively. Other algorithms which are available for comparison have high injection of powers. Figure 14a shows the real power losses in the system after implementation of DG with different algorithms. Figure 14b shows the reactive power losses in the system after implementation of DG with different algorithms. Figure 14c shows the multi objective function value for different algorithms. Figure 14d shows the percentage power loss reduction in the system with different algorithms after implementation of DG. Figure 15 shows the comparison of voltage profiles for different algorithms.

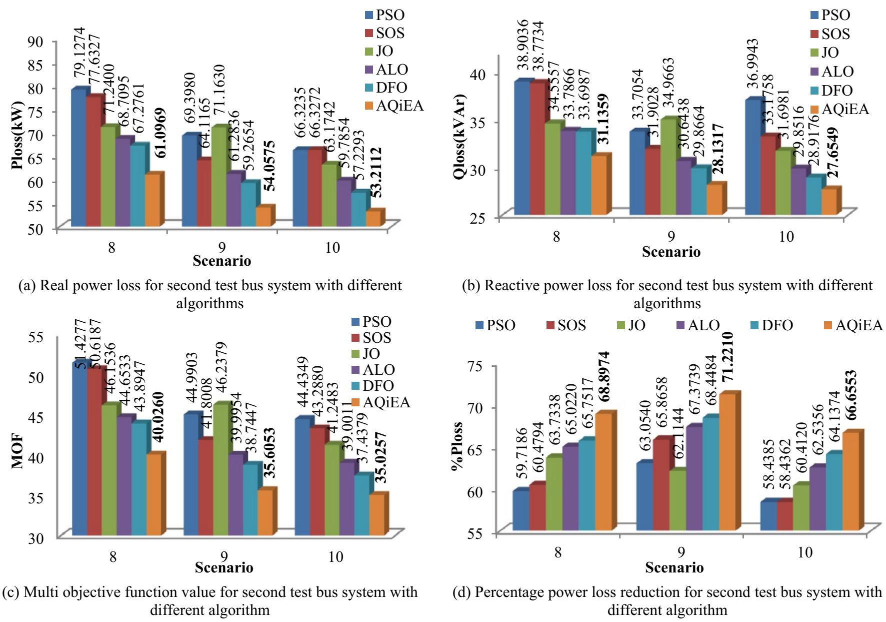
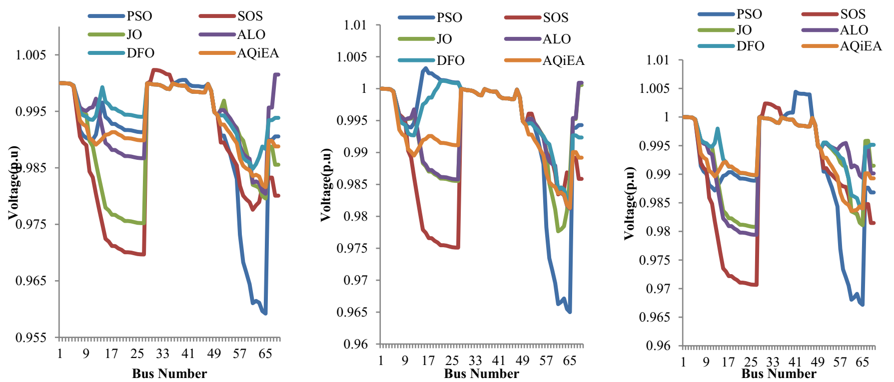


Fig. 14 Real and reactive power loss, multi objective function value and percentage power loss reduction for second test bus system with different algorithms

5 Discussions

Distribution network accounts for majority of power losses in power system because of high resistance to reactance ratio. Many techniques are implemented in distribution to reduce the power losses. In present scenario, DG which injects active or reactive power into the system has gained more importance to reduce the power losses. DGs are placed near to load centers the transmission loss and power losses produced by the distribution system during distribution are reduced. DGs are mainly used in distribution system due to its ease of implementation and environmental friendly technologies. Many researchers have solved this important and challenging optimization problem with constant power load model. Constant power load models are fixed loads which are independent of voltage and don't vary with time. However, in practical distribution network loads are mainly dependent on magnitude of supply voltage. Few authors have also solved this optimization problem with voltage dependent load models such as constant impedance load (CZ), constant current load (CI), industrial load (IL), commercial load (CL) and residential load (RL). The above mentioned loads are dependent on voltage but performances of ZIP loads are not considered. In this study, an investigation has been performed to find the effect of DG on ZIP loads. Seven different ZIP load models are considered. Two IEEE benchmark test bus system are used to test the effectiveness of proposed algorithm. Two cases are created to study the effect of DG. First case is used to study the effect of DG on seven different ZIP load models with ten different scenarios. In addition to power losses, performance indices are also added. It has been observed from results that optimal location of DG for first test bus system is similar for scenario I, II, IV, V and X. The optimal locations for these scenarios are 30, 24 and 14. The remaining scenarios such as scenario III, VI, VII, VIII and IX are also having same optimal location 30, 13 and 24. The optimal locations of DG for all scenarios are similar, which is mainly due to the linear change in load. The optimal sizing of DG is changing for every scenario. After implementing DG power losses are reduced to minimum value. Similarly, for second test bus system the optimal location of DG



(a) Voltage Profile Improvement for Scenario VIII (b) Voltage Profile Improvement for Scenario IX (c) Voltage Profile Improvement for Scenario X

Fig. 15 Voltage profile improvement with different algorithms on second test bus system is similar for scenario I, VI with location 60, 15, 61 and optimal location of DG is similar for scenario II, IV, VIII with location 60, 16, 61. The remaining scenarios have different optimal location i.e., scenarios III, V, VII, IX and X have different locations. After implementing DG, reduction in RPLI, RePLI for both test bus are observed. It has been observed from tabulated results that the total power injected by DG into the system for both test bus systems are always less than acceptable limits. The total penetration of DG for all scenarios of first test bus system is 77% which creates a percentage power loss reduction of 62%. In one scenario it has been observed that with 75% penetration creates a power loss reduction of 71%. Similarly, for second test bus system the penetration of DG for all scenarios is below 60%, which creates a percentage power loss reduction of 65%. In one scenario it has been observed that with 58% penetration creates a power loss reduction of 75%.

In second case, the performance of AQiEA is compared with other sate of art techniques. Multi objective function which involves real power loss, reactive power loss, voltage deviation index and power injected by DG is used test the effectiveness of proposed algorithm with other state of art techniques. It has been observed from tabulated results that AQiEA is performing better in all aspects such as power losses, power injected by DG, multi objective function and percentage power loss reduction for both test bus systems in comparison with other state of art techniques. The multi objective function value and percentage power loss reduction value for scenario VIII with different algorithms for first test bus system is represented as follows AQiEA, DFO, ALO, JO, PSO and SOS. Scenario IX has multi objective function value and percentage power loss reduction values with different algorithms are represented as follows AQiEA, DFO, ALO, JO, SOS and PSO. Similarly for scenario X the multi objective function value and percentage power loss reduction values with different algorithms are represented as follows AQiEA, ALO, DFO, JO, PSO and SOS. The multi objective function value and percentage power loss reduction value for second test bus system with scenario IX by implementing DG on different algorithms are represented as follows AQiEA, DFO, ALO, SOS, PSO and JO. Scenario VIII and X has multi objective function value and percentage power loss reduction values with different algorithms are represented as follows AQiEA, DFO, ALO, JO, SOS and PSO. In this study, AQiEA is used to find the optimal location and capacity of DG. AQiEA is relatively new and efficient evolutionary intelligent techniques implemented on many engineering optimization problems. AQiEA uses two Q-bits which are entangled with one another and represented in quantum system with respect to the superposition of basis state which increases the population diversity. Tabulated results show the,effect of DG on different ZIP load models with performance indices. Tabulated results demonstrate that, AQiEA has better performance as compared with other state of art techniques.

6 Conclusions

In this study an investigation has been performed to reduce the power losses with implementation of DG on ZIP load models. Two different Cases are considered to reduce the power losses with integration of DG into distribution system. In addition to power losses, performance indices are also used to study the effect of DG on ZIP load models. First Case uses seven different ZIP load models and ten different scenarios to reduce the power losses. In each scenario independent implementation of ZIP load model has been considered to reduce the power losses. However, in practical distribution network, consumers at load centre use a combination of all ZIP load models. In this study, scenario VIII, IX and X uses combination of all ZIP load models which reflects that the study is conducted on practical load models. In addition to power losses, performance indices are also considered in all scenarios before and after implementation of DG. It has been observed from tabulated results that power losses are reduced to minimum value if DGs are integrated into distribution system. A comparative analysis has been done for all ten scenarios with performance indices before and after implementation of DG. Optimal location and capacity of DG is difficult combinatorial optimization problem which includes continuous and discrete variables. A quantum inspired evolutionary algorithm i.e., AQiEA has been used to find the optimal location and capacity of DG. The proposed algorithm uses probabilistic representation with Q-bits and a Quantum Rotation inspired Adaptive Crossover operator, which is used as a rotation gate for better convergence. The effectiveness of proposed algorithm is tested on two different IEEE benchmark test bus systems with three different scenarios. In Case-B, the effectiveness of AQiEA is compared with other algorithms. Multi objective function is also used. Tabulated results demonstrate that AQiEA has high reduction in power losses as compared with other algorithms.

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Authors and Affiliations

Gopisetti Manikanta[1] · Ashish Mani[1] · Hemender Pal Singh[1] · Devendra Kumar Chaturvedi[2]

✉ Gopisetti Manikanta
manikanta.250@gmail.com

Ashish Mani
amani@amity.edu

Hemender Pal Singh
hpsingh2@amity.edu

Devendra Kumar Chaturvedi
dkc.foe@gmail.com

[1] Department of Electrical and Electronics Engineering, ASET, Amity University, Noida, Uttar Pradesh, India

[2] Department of Electrical Engineering, F.O.E, Dayalbagh Educational Institute (Deemed University), Dayalbagh, Agra, India