Binary Bat Algorithm for Optimal Operation of Radial Distribution Networks

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Abstract: The amount of power losses in the lines of distribution topology are very significant and they make the bus voltages of the system poor. This leads to the development of smart distribution system configurations. Therefore, this paper highlights an efficient network topology approach for the optimal utilization of radial distribution systems (RDSs) by applying the network reconfiguration (NR) and allocating the distribution static compensator (D-STATCOM), distributed generation (DG) units, and electric vehicle charging stations (EVCSs). The proposed RDS problem is solved subjected to the power balance, location, and sizes of D-STATCOM and DG, and voltage constraints. Here, the binary bat algorithm (BBA) is implemented for solving DG, D-STATCOM, and EVCSs allocation in RDS as well as the network reconfiguration (NR). The developed methodology has been tested on IEEE 33 bus RDS.

Keywords: Distribution static compensator; Network reconfiguration; Power loss; Evolutionary algorithms; Distributed generation; Electric vehicles.

1. Introduction

Distribution system is an important section of the power network and is operated at various loading conditions. The main aim of any power system is to deliver reliable and economically viable power demand to the consumers. The structure of distribution systems is complex in nature and it increases more in the case of increased load density. However, the power losses in a radial distribution system (RDS) are much higher when compared to the transmission networks. In order to minimize the losses, several methodologies have been developed in the RDSs including the optimal allocation of distributed generations (DGs), shunt capacitors, and optimal network reconfiguration (ONR). All these approaches use a different process of implementation for power loss reduction and they have their own impact on the optimal operation of RDS [1, 2]. As the renewable energy sources (RESs) are economical, sustainable, and environmentally friendlier, all the governments are investing plans and investments to improve RES utilization as much as possible.

The distributed generation (DG) is a resource for generating the electrical energy that takes place near the load centers and is suitable to meet the increased demand for electrical energy. The merits of placing DG schemes are enhancement in voltage profile, minimization of line-losses, maximized efficiency, improvement in reliable power flow, ease to integrate, reduction in the cost of generation, etc. To ensure the reliable, efficient, and stable operation of a distribution network, planning for DG integration through the RESs is essential. The use of RESs has been growing rapidly in the last decades. However, the maturity in RESs has reduced the maintenance and installation costs [3]. Nowadays, all the developing countries are towards the integration of large-scale RESs into the grid. Due to the reduced cost of RESs and land availability, several countries are moving towards RESs investments. In recent years, the DGs are encouraged to get integrated widely in the RDSs [4]. Several benefits such as reduced power losses, enhanced bus voltages, and environmental benefits make the DG integration popular.

The four pillars of electric mobility include electric vehicles (EVs), charging and swapping infrastructure, batteries, and other factors such as manufacturing capacity, research, and development, etc. The grid integration of EVs provides an improvement in the voltage profile of

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the entire system and auxiliary support [5, 6]. The present work focuses on the optimal allocation of D-STATCOMs and DGs for loss minimization in RDSs. Here, the reconfiguration problem is solved in the presence of D-STATCOM, DG units, and electric vehicle charging stations (EVCSs). The viability and efficacy of the proposed method are tested on a standard 33-bus RDS for six different cases of network reconfiguration (NR) along with DG, D-STATCOM, and EVCSs allocation.

A. Related Work

In the present deregulated scenario, both the distribution and generation companies are dedicated to their own function, which avoids the monopoly of power system brokers and creates competition between them. This forces the power utilities to fulfill the energy demand of the consumer at a reasonable cost [7]. The optimization of NR and DG allocation at a time is more relevant, and hence this work presents an optimal methodology to address the issues of NR along with DG allocation for the consideration of loss minimization objective. Various solution methods for solving this problem include heuristic-based, population-based metaheuristic, and AI-based approaches. Among these categories, population-based metaheuristic approaches are very popular and guarantee a globally optimal solution. A sequential switch exchange and opening technique is proposed in reference [8] to minimize losses through NR with and without the integration of DGs. In reference [9], an optimization problem of RDS with the energy storage has been presented by using the second-order mixed-integer cone programming approach. The particle swarm optimization (PSO) algorithm is proposed in reference [10] and a fractal search algorithm is proposed in reference [11] for optimal reactive power dispatch as well as NR to optimize the power losses and to minimize the voltage drop.

An overview of voltage control approaches on RDSs interconnected with the DG is presented in reference [12], and the suggestions are reported by optimally using the DG units and enhancing the network voltage stability. A competent optimization methodology based on a grey wolf optimization technique for the allocation of multiple DGs in RDSs is proposed in [13]. An overview of hosting capacity in RDSs with their developments in hosting capacity, limitations, and enhancement approaches has been presented in reference [14]. A new multi-objective technique for multi-objective-based NR with optimal allocation of DGs has been proposed in [15]. A modified stochastic fractal search technique is described in [16] for optimal location and sizing of shunt capacitors for RDSs with 33, 69, and 85 bus RDSs. In reference [17], a new tree seed technique is developed for the solution of the reactive power dispatch problem in the RDS.

From the above literature review, it can be observed that several researchers have proposed various approaches for solving the NR problem on different test systems. The NR problem was considered as a complex decision-making process for the optimal operation of RDS. Due to the combinatorial nature of the NR and DG allocation problem needs complicated mathematical techniques. In the literature, several researchers formulated and solved the NR and DG allocation problem by using various evolutionary-based algorithms such as genetic algorithm, PSO, differential evolution, simulated annealing, ant colony algorithm, harmony search algorithm, bacterial foraging algorithm, firework algorithm, and cuckoo search algorithm. However, for all these algorithms the selection and parameter tuning is complex. Therefore, in this paper a binary bat algorithm is used as its performance doesn't depend on the selection and parameter tuning. All the reported works in the literature solve only the NR and DG allocation in the RDS, and they don't consider the electric vehicle charging stations (EVCSs) in their optimization. Therefore, this paper solves the NR problem along with the optimal allocation of DG units, D-STATCOMs and EVCSs.

B. Scope and Contributions of this Work

Higher penetration and improper allocation of DGs, EVCSs, and D-STATCOMs significantly impact the operation of RDSs. Therefore, the optimal allocation along with NR is an important issue in the present scenario for delivering optimal real and reactive power to the utility grid. Power distribution companies need more efficient planning strategies in order to provide electricity to their consumers as economically as possible and with a good level of power quality and reliability. With the current deregulation of power sectors, the traditional expansion of additional substations to meet the forecasted load growth is not economical and the utilities need alternative technologies like optimal integration of DGs, NR, and simultaneous allocation of DG allocation and NR. The major objectives and contributions of the proposed work are presented in this manuscript are highlighted as follows:

- Proposes an efficient approach for optimal allocation of D-STATCOM, DG is an RDS along with optimal NR.
- Proposed optimization problem is solved by using the binary bat algorithm (BBA).
- Proposed approach offers significant solution quality for all scenarios considered in this work in terms of minimum voltage and power loss over other competitive algorithms existing in the literature.
- Proposed methodology is successfully verified on the 33-bus RDS considering six different cases of NR, DGs, D-STATCOM, and EVCSs allocation.
- The analysis shows that the NR along with simultaneous DG, D-STATCOM, and EVCSs have a more substantial impact than considering the cases separately.

2. Distribution Load Flow (DLF)

One of the major technical malfunctions in RDS is due to low X/R ratio and low voltage level, which leads to poor voltage profile or voltage regulation and higher power loss in the system. To meet the increasing load demand, the RDSs have to be maintained, upgraded, and operated with better planning incorporating smarter technologies [18]. Therefore, the RDSs are required to adopt some efficient planning strategies for additional active and reactive power support designed explicitly to meet their optimum performance and stagger their future expansion plans. Figure 1 depicts the typical structure of RDS.

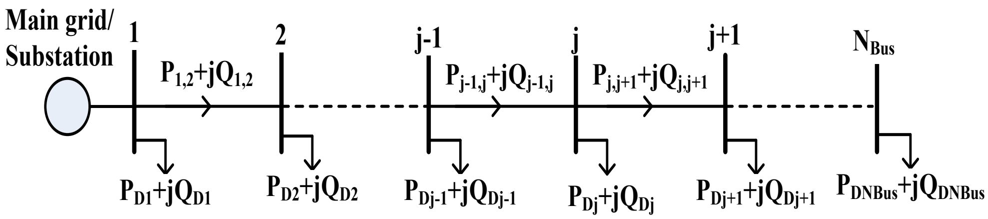

Figure 1. Typical structure of RDS.

Here, the DLF is developed in reference [19] is utilized, which is an iterative-based approach that uses the fundamental laws of electrical circuits. In the backward sweep method, the d-component of branch currents can be determined by using,

$$I_{dj} = \frac{P_{Dj}cos\varphi_{j-1} + Q_{Dj}sin\varphi_{j-1}}{V_{j-1}} \tag{1}$$

Where P_{Dj} and Q_{Dj} are the real and reactive power demands at bus j. The q-component of branch currents can be determined by using [20],

$$I_{qj} = \frac{Q_{Dj}cos\varphi_{j-1} - P_{Dj}sin\varphi_{j-1}}{V_{j-1}} \tag{2}$$

In the forward sweep method, the magnitude and phase angle of bus voltages are determined by using,

$$V[Re(j)] = \sqrt{V_d^2[Re(j)] + V_q^2[Re(j)]} \tag{3}$$

$$\varphi[Re(j)] = tan^{-1}\left[\frac{V_q(Re(j))}{V_d(Re(j))}\right] \tag{4}$$

Where

$$V_d(Re(j)) = V_d[Se(j)] - R[Re(j)]I_d[Re(j)] - X[Re(j)]I_q[Re(j)] \quad (5)$$

$$V_q(Re(j)) = V_q[Se(j)] - X[Re(j)]I_d[Re(j)] + R[Re(j)]I_q[Re(j)] \quad (6)$$

3. Problem Formulation

The discrete nature of DG and D-STATCOM location, discrete/continuous nature of DG and D-STATCOM sizes, and discrete nature of NR will make the proposed problem much more complex. Different techniques proposed in the literature address the challenges related to the RDS of different systems and operating constraints [21]. Numerous optimization techniques are proposed in the literature considering the various classical, meta-heuristic, and hybrid algorithms.

A. Modeling of EVCSs, D-STATCOM, and DG

Optimal allocation of EVCSs in the RDS is an important problem to be determined. Figure 2 depicts the modeling of EVCSs in RDS [22]. The power demand (P_D^{EVCS}) of EVCS depends on the various factors such as charging and discharging efficiencies and rates, and vehicle to grid (V2G) and grid to vehicle (G2V) modes of operation of electric vehicles (EVs). The power demand of EVCS at a particular charging is given by,

$$P_D^{EVCS} = (N_{EV}P_{G2V}\eta_C R_c) - (N_{EV}P_{V2G}\eta_d R_d) \quad (7)$$

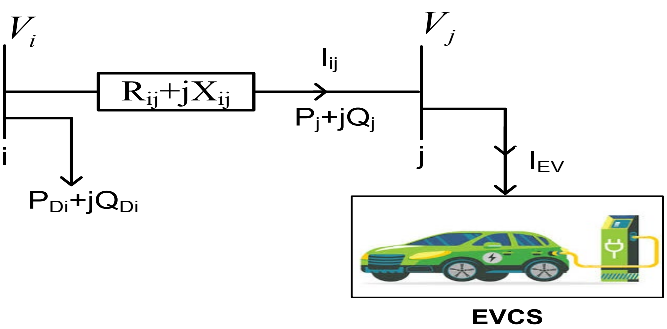

Figure 2. Modeling of EVCSs in RDS.

Figure 2 depicts the modeling of D-STATCOM in RDS. The amount of reactive power support from the D-STATCOM ($Q_{D-STATCOM}$) is given by,

$$Q_{D-STATCOM} = \frac{V_m^2}{X_k} - \frac{V_m V_n}{X_k}\cos\delta \quad (8)$$

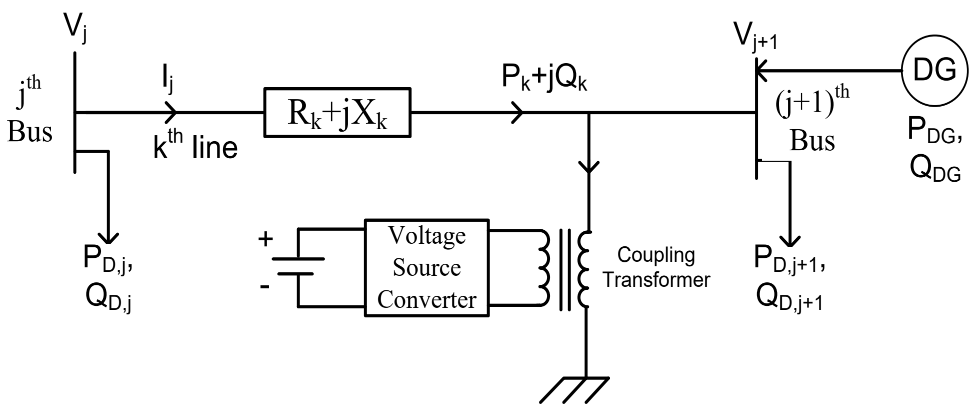

Figure 3. Modeling of D-STATCOM and DG in an RDS.

B. Objective Function and Constraints

The active and reactive power losses in a line that is connected between bus a and bus b can be represented by [23],

$$P_{a,b}^{loss} = \left(\frac{P_{a,b}^2 + Q_{a,b}^2}{|V_a|^2}\right) \times R_{a,b} \tag{9}$$

$$Q_{a,b}^{loss} = \left(\frac{P_{a,b}^2 + Q_{a,b}^2}{|V_a|^2}\right) \times X_{a,b} \tag{10}$$

Total active power loss incurred in all the lines (P_T^{loss}) are represented by [20],

$$P_T^{loss} = \sum_{a=1}^{N_B} \left(\frac{P_{a,b}^2 + Q_{a,b}^2}{|V_a|^2}\right) \times R_{a,b} \tag{11}$$

The minimization of active power loss objective can be represented by [21],

$$f = minimize\ (P_T^{loss}) \tag{12}$$

In order to find valid solutions to the NR and the allocation of renewable-based DG units in the distribution network, the following equality and inequality constraints must be considered.

C. Equality Constraints

These constraints of real and reactive powers are expressed as [24],

$$P_D = \sum_{i=1}^{N_{DG}} P_{DG,i} + P_G^{Grid} \tag{13}$$

$$Q_D = \sum_{i=1}^{N_{DG}} Q_{DG,i} + Q_G^{Grid} \tag{14}$$

D. Inequality Constraints

DG Power Constraints:

Power limits on DG units can be expressed as [25],

$$N_{DG,k}^{min} P_{DG,k} \leq N_{DG,k} P_{DG,k} \leq N_{DG,k}^{max} P_{DG,k} \tag{15}$$

$$N_{DG,k}^{min} Q_{DG,k} \leq N_{DG,k} Q_{DG,k} \leq N_{DG,k}^{max} Q_{DG,k} \tag{16}$$

$N_{DG,k}$ is number of DG units that are connected at bus k. The initial size of DG units are generated randomly by using,

$$P_{DG,k} = P_{DG,k}^{min} + rand\left(P_{DG,k}^{max} - P_{DG,k}^{min}\right) \tag{17}$$

Where P_{DG}^{max} is the maximum amount of power output from DG and it is calculated by using the capacity factor (CF), which is expressed by,

$$P_{DG}^{max} = \frac{P_{DG}^{avg}}{CF} \tag{18}$$

Constraints on DG location:

DGs can be installed at any bus in the system, and it can be expressed as,

$$2 \leq DG_{location} \leq N_{bus} \tag{19}$$

And also the DG locations that are selected must be distinct and it can be represented by,

$$DG_{location,i} \neq DG_{location,j} \qquad (i,j) \in N_{bus} \tag{20}$$

Bus voltage constraints:

These constraints represent the voltage limit at each bus in the system and it can be represented by [26],

$$V_{b,i}^{min} \leq V_{b,i} \leq V_{b,i}^{max} \tag{21}$$

Where $V_{b,i}$ is the ith node voltage.

D-STATCOM constraints:

The constraints on the reactive power support from the D-STATCOM are expressed by,

$$Q_{D-STATCOM} \leq (Q_D + Q_{loss}) \quad (22)$$

$$0 \leq Q_{D-STATCOM} \leq Q_{D-STATCOM}^{max} \quad (23)$$

Thermal constraints:

The thermal constraint of substations and feeders describes the maximum allowed apparent power (S_{grid}^{max}) and currents flowing through a substation transformer and feeders in the distribution system, and they are expressed as,

$$S_{grid} \leq S_{grid}^{max} \quad (24)$$

$$I_{b,k} \leq I_{b,k}^{max} \qquad k = 1,2, \dots, N_{br} \quad (25)$$

Where $I_{b,k}$ and $I_{b,k}^{max}$ are k[th] line current and maximum allowable current, respectively.

Capacity constraint of EVCSs:

The maximum charging capacity (C_{EVCS}^{max}) is restricted by,

$$C_{EVCS} \leq C_{EVCS}^{max} \quad (26)$$

Reliability/Topological constraint:

It is required to ensure that the radial and connected status of the RDS, and it is represented by,

$$N_{br} = N_b - 1 \quad (27)$$

4. Proposed Solution Methodology

The proposed RDS problem is solved by using the nature-inspired binary bat algorithm (BBA). The natural behavior of bats has inspired researchers to develop a technique by considering its ability to find food. The number of bats/variables has been initialized equivalent to the total number of features [27]. All possible combinations of features have been validated and the set with the best result has been chosen as the optimal feature set. Bats use sound energy while searching their prey among their camp. In designing the bat algorithm (BA), the position and velocity of each bat have been considered. While hunting, the emission of ultrasonic sound has been increased thereby decreasing the loudness [28]. In BA, the position of each bat is based on its frequency. The frequency, velocity, and position of bats can be determined by using [29, 30],

$$f_i = f^{min} + \delta(f^{max} - f^{min}) \quad (28)$$

$$v_i^k = v_i^{k-1} + f_i(p_i^k - p^*) \quad (29)$$

$$p_i^k = p_i^{k-1} + v_i^k \quad (30)$$

Where δ is a random number between 0 and 1. BBA is the discrete (binary) version of BA, and it utilizes the sigmoid function for confining the new position of bat's to binary values by using [29],

$$\mathrm{S}(v_i^k) = \frac{1}{1 + e^{-v_i k}} \quad (31)$$

In the BBA, the position is updated by using,

$$p_i^k = \begin{cases} 1 & if\ \mathrm{S}(v_i^k) > \sigma \\ 0 & Otherwise \end{cases} \quad (32)$$

Where σ represents a uniform distribution [0, 1]. The next possible position of bat represented by [30],

$$p_{new} = p_{old} + \varepsilon L^k \quad (33)$$

Where L^k is average loudness of all the bats, and $\varepsilon \in [-1, 1]$. The pulse rate is changed by using [31],

$$r_i^{k+1} = r_i^0[1 - e^{-\gamma k}] \quad (34)$$

The loudness modulation is changed by using,

$$L_i^{k+1} = \alpha L_i^k \quad (35)$$

Where α and γ are the constants [32]. The complete solution methodology by using BBA has been depicted in figure 4.

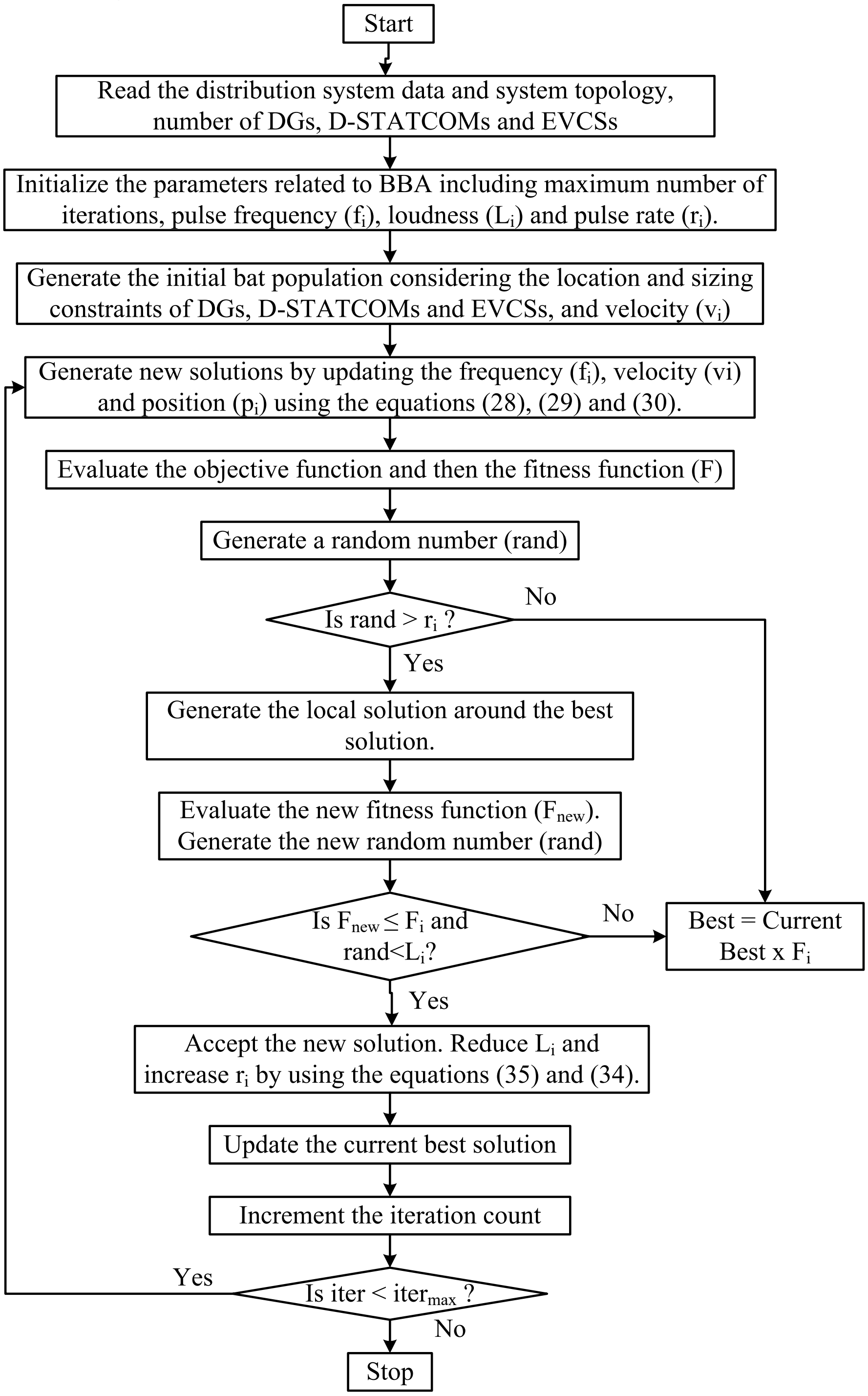

Figure 4. Solution methodology using binary bat algorithm (BBA).

A. Implementation of BBA for ONR and optimal allocation of DGs, D-STATCOMs and EVCSs

The steps employed for power loss minimization objective using the proposed BBA is presented below.

Step 1: Read the distribution system data and system topology, maximum number and sizes of DGs, D-STATCOMs and EVCSs. Initialize the parameters related to BBA including maximum number of iterations, pulse frequency (f_i), loudness (L_i) and pulse rate (r_i).

Step 2: Generate the initial bat population considering the location and sizing constraints of DGs, D-STATCOMs, EVCSs, and velocity (v_i) which satisfies all the constraints.

Step 3: Run the DLF program and calculate power loss for each bat.

Step 4: Evaluate the objective function and then the fitness function (F).

Step 5: Generate new solutions by updating the frequency (f_i), velocity (vi) and position (p_i) using the equations (28), (29) and (30).

Step 6: Evaluate the new fitness function (F_{new}). Generate the new random number (rand).

Step 7: Check $F_{new} \leq F_i$ and rand<L_i. If yes, accept the new solution. Reduce L_i and increase r_i by using the equations (35) and (34). Update the current best solution.

Step 8: Check for the stopping criterion. If yes, display the power loss value and corresponding open switches, and optimum locations and sizes of DGs, D-STATCOMs and EVCSs. Otherwise, repeat the steps 3 to 7.

5. Results and Discussion

To validate and demonstrate the results obtained by using BBA in solving the proposed RDS problem. The algorithm is applied on 33 bus RDS with 12.6 kV base voltage. It consists of 32 sectionalizing and 5 tie line switches. Sectionalizing switches from 1-32 are normally closed, and the tie-switches 33-37 are opened. The maximum number of DGs, D-STATCOMs, and EVCSs that can be integrated is restricted to three, one, and one, respectively for this 33 bus RDS. The maximum size of DG, D-STSTACOM, and EVCS for the allocations have been limited to 2000 kW, 2000 kVAr, and 3000 kW, respectively. To analyze the proposed methodology, 6 case studies are simulated, and they are:

- **Scenario 1**: Base case/without any optimization
- **Scenario 2**: With only NR
- **Scenario 3**: With only DG allocation
- **Scenario 4**: With both NR and DG allocation
- **Scenario 5**: With both NR and D-STATCOM
- **Scenario 6**: With simultaneous NR, DG, D-STATCOM, and EVCS allocations

A. Scenario 1

Scenario 1 is the base case condition (i.e., before the NR). In this scenario, switches 33 to 37 are opened and the obtained system losses are 202.66 kW. Minimum voltage is obtained at bus 18 of 0.9131 p.u., and it is reported in Table 1. The initial configuration of 33 bus RDS is presented in figure 5.

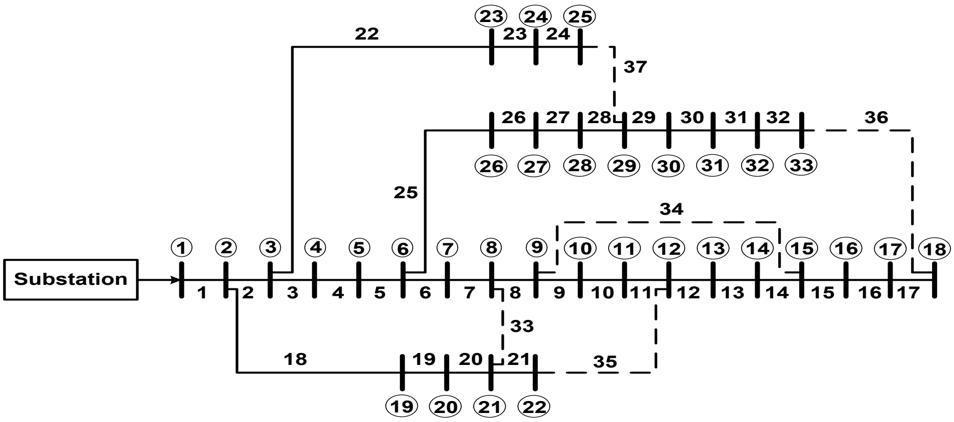

Figure 5. Topology of 33 bus RDS (Scenario 1).

B. Scenario 2

In this scenario, only NR is performed. Here, the tie switches 7, 9, 14, 32, and 37 are opened. The topology of the RDS after the NR is shown in figure 6. After the NR, the voltages in the system are improved. Bus voltages before and after the NR is depicted in figure 7. The power losses incurred in this scenario are 139.48 kW and they are 31.18% less than the losses obtained in scenario 1, and they are presented in Table 1. The minimum voltage reported in this scenario is 0.9402 p.u. at bus number 32.

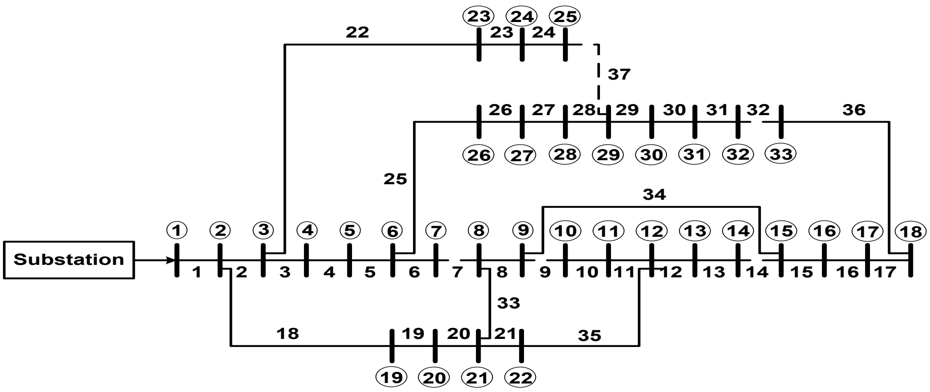

Figure 6. Topology after NR of 33 bus RDS (Scenario 2).

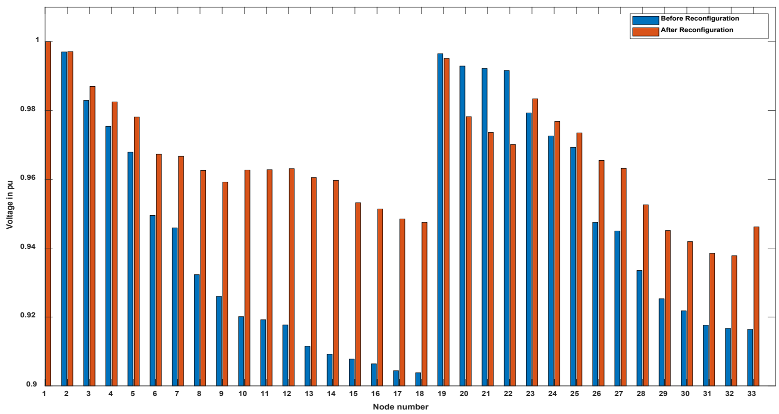

Figure 7. Bus voltages before (scenario 1) and after NR (scenario 2).

C. Scenario 3

In this scenario, the optimization is conducted by considering the only optimal allocation of DG units, and the results are reported in Table 1. Obtained optimal sizes of DG units are 780.5 kW, 1120.6 kW, and 1170.3 kW, respectively at buses 13, 23, and 29. Therefore, the total capacity of DGs is 3071.4 kW. Minimum losses incurred are 70.96 kW, and they are 64.98% less when compared to scenario 1 (base case configuration). Minimum voltage has occurred at bus number 32 with the voltage of 0.9402 p.u.

Table 1. Simulation results for scenarios 1, 2, and 3.

	Scenario 1	**Scenario 2**	**Scenario 3**
Opened/tie switches	33, 34, 35, 36, 37	7, 9, 14, 32, 37	33, 34, 35, 36, 37
DG size in kW (bus number)	-----	-----	780.5 (13), 1120.6 (23), 1170.3 (29)
Total size of DG (kW)	-----	-----	3071.4
D-STATCOM size in KVAr (bus number)	-----	-----	-----
Power loss (kW)	202.66	139.48	70.96
Power loss reduction (%)	-----	31.18	64.98
Minimum voltage (V_b^{min}) in p.u (bus number)	0.9131 (18)	0.9402 (32)	0.9688 (32)

D. Scenario 4

In this scenario, both the DG allocation and NR are simulated, and the results are presented in Table 2. Here, the NR has resulted in the opened tie lines of 7, 14, 11, 17, and 28. The obtained optimal allocation DG units have capacities of 1032.6 kW, 1184.2 kW, and 862.8 kW at locations 18, 24, and 29. The total capacity of DGs is 3079.6 kW. The minimum power loss incurred is 56.58 kW, and it is 72.08% less when compared to scenario 1. The obtained minimum voltage has the value of 0.9762 p.u. at bus 18.

Table 2. Simulation results for scenarios 4, 5, and 6.

	Scenario 4	**Scenario 5**	**Scenario 6**
Opened/tie switches	7, 14, 11, 17, 28	7, 14, 9, 32, 37	6, 14, 11, 17, 28
DG size in kW (bus number)	1032.6 (18), 1184.2 (24), 862.8 (29)	-----	1025.2 (8), 1178.5 (24), 836.8 (29)
Total size of DG (kW)	3079.6	-----	3040.5
D-STATCOM size in KVAr (bus number)	-----	1046.4 (31)	1030.0 (31)
EVCS size in kW (bus number)	-----	-----	2162.5 (21)
Power loss (kW)	56.58	98.83	56.10
Power loss reduction (%)	72.08	51.23	72.32
Minimum voltage (V_b^{min}) in p.u (bus number)	0.9762 (18)	0.9482 (33)	0.9773)

E. Scenario 5

In this scenario, both the NR and D-STATCOM allocation have been simulated at a time. The obtained results are reported in Table 2. The obtained results have the NR with the opened lines 7, 14, 9, 32, and 37, and a D-STATCOM is placed at bus number 31 with a capacity of 1046.4 kVAr. The minimum loss incurred in this scenario is 98.83 kW, and this has resulted in a 51.23% reduction in losses when compared to losses incurred in scenario 1. The obtained minimum voltage has the value of 0.9482 p.u. at bus 33.

F. Scenario 6

In this scenario, the optimization is performed by simultaneous NR and allocation of D-STATCOM, DG, and EVCSs. The opened lines, in this case, are 6, 14, 11, 17, and 28. The obtained DG sizes are 1025.2 kW, 1178.5 kW, and 836.8 kW at buses 8, 24, and 29, respectively. The total size of DG units is 3040.5 kW. The size of D-STATCOM is 1030.0 kVAr at bus 31. The EVCS is located at bus 21 with the size of 2162.5 kW. The minimum power loss reported in this scenario is 56.10 kW, and it is 72.32% less when compared to power losses obtained in scenario 1.

It is observed that the optimal allocation of DGs, D-STATCOM, and EVCS has significantly reduced power loss and improved the voltage profile of the 33 bus RDS. The power losses incurred in scenario 2 are 139.48 kW and they are 31.18% less than the losses obtained in scenario 1 (base case configuration). The minimum losses incurred in scenario 3 are 70.96 kW, and they are 64.98% less when compared to scenario 1. The minimum power loss incurred in scenario 4 is 56.58 kW, and it is 72.08% less when compared to scenario 1. The minimum loss incurred in scenario 5 is 98.83 kW, and this has resulted in a 51.23% reduction in losses when compared to losses incurred in scenario 1. In scenario 6, the overall power loss is reduced to 56.10 kW which is 72.32% less when compared to power losses obtained in scenario 1. All the above results and analysis show that the simultaneous NR, DG, D-STATCOM, and EVCSs have a more substantial impact than considering the cases separately.

6. Conclusions

This paper proposes an efficient methodology for the optimal location of distributed generation (DG) units, D-STATCOM, and electric vehicle charging stations (EVCSs) as well as the network reconfiguration (NR) in the distribution systems. The proposed problem is solved by using the binary bat algorithm (BBA). The proposed algorithm has been implemented on 33 bus RDS. The results and analysis show that simultaneous NR, DG, D-STATCOM, and EVCSs have a more substantial impact than considering the cases separately. Modeling and developing a dynamic and multi-objective stochastic model to handle the uncertainties of renewable energy sources and load in simultaneous NR and DG allocation problems by considering the geographical location of the practical distribution system is a scope of future work. Since distribution systems considered in this work are balanced RDSs hence they can be extended for unbalanced systems.

7. Acknowledgment

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