1. Introduction

The technical and economical aspects of the distribution systems affect the system reliability, line loadings, losses, etc. The technological developments in the era of solar and wind energy and some more promising technologies increases the importance of installation in auxiliary generation nearer to the load centres. Since, these are located at load centres; the transmission cost gets decreased with little installation time and with increased reliability of the supply. To achieve these benefits, the DG(s) must be optimally placed (i.e. location and size) in a given system. Generally, this problem is non-linear, stochastic optimization problem subjected to certain system constraints. Improper allocation of DG(s) affects the system reliability.

Recently several authors have proposed swarm intelligence based optimization techniques to solve optimization problem to obtain optimum DG location with size. A very few authors have concentrated in finding an optimal location for DG to get maximum benefit based on power losses. From, the careful review of the literature, it has been identified that, most of the literature is confined to identify an optimal location based on single objective optimization process. Here, there is a scope to formulate a methodology to identify an optimum number of DGs in a given system to get maximum benefit. Similarly, in some literature, multi objective optimization problem based on weighted sum method, neural network based algorithms to place the DGs in a given system. From the analytical results of single objective optimization, it is identified that,
minimization/maximization of one of the objectives results in maximizes/minimizes the value of the other objectives. In real, it requires a lot of practice to identify an optimal size of DG to satisfy multiple objectives while satisfying system constraints.

Some of literature presents methodology to solve multi objective optimization problem. But these methods are based on the conventional optimization techniques such as particle swarm optimization, genetic algorithms, etc. These methods result only one compromised solution rather than the operators’ requirement and are suffered from premature convergence problem. Sometimes, the result may mislead the operation and costs a lot. Hence, it is necessary to develop a methodology to solve multi objective optimization problem.

Keeping all these points in mind, a methodology to identify an optimal location to install DG with active power injections in a given system based on system loss sensitivity index analysis. Using this information, the number of DGs is also identified. After this, to solve single objective optimization problem with net savings, voltage deviation and section current index as objectives, a novel optimization algorithm namely modified cuckoo search algorithm is proposed. With this, the economical and technical aspects of the distribution system are analyzed. To extend the problem more realistic, two and three objectives multi objective optimization problem is solved while satisfying system equality and in-equality constraints. For this, a novel methodology based on non-dominated sorting and fuzzy decision approaches is developed. The developed methodologies are carried out on standard bench mark functions, 15-node, 33-node and 69-node radial distribution systems with supporting numerical, graphical and validations.

2. Problem Formulation

Generally, the optimization problem can be expressed as

$$\text{Min} / \text{Max} \quad J_\text{p}(x,u)$$

Where, ‘p’ is the number of objectives, ‘x’ and ‘u’ are the state and control vectors. In brief, these can be expressed as

$$x^T = \{V_1, V_2, \ldots , V_N\}; \quad u^T = \{P_{DG_1}, P_{DG_2}, \ldots , P_{DG_{ng}}\}$$

Here, ‘N’ is the total number of nodes; ‘ng’ is the total number of DGs.

To solve the optimization problem, the following three objectives namely savings, voltage deviation and Section Current Index (SCI) are formulated and are optimized while satisfying system equality and in-equality constraints.

2.1 Objectives Formulation

In this paper, economic aspects of the distribution system are enhanced by maximizing the savings objective in the presence of DG(s). In the same way, the technical aspects of the system are enhanced by minimizing the voltage deviation and SCI objectives in the presence of DG(s).

2.1.1 Maximization of Savings ($)

This objective is used to maximize the net savings in a given system in the presence of DG(s). The mathematical expression used to calculate net savings with DG(s) is

$$\text{max} \left( J_{\text{savings}}^{\text{DG}} \right) = \text{max} \left( B_{\text{rd}} + B_{\text{rf}} + B_{\text{se}} - C_{dg} \right)$$

where, $B_{\text{rd}}$, $B_{\text{rf}}$, $B_{\text{se}}$ are the benefits due to reduced demand (kW), released feeder capacity (kVA) and saving in energy losses (kWh) respectively. ‘C_{dg}’ is the the cost of installation of DG(s) in ‘$’.

The individual terms can be expressed in detailed as follows:

(a) Benefit due to reduced demand

$$B_{\text{rd}} = \Delta B_{\text{rd}} \times C_{\text{rd}} \times I_B_{\text{rd}}$$

Here, ‘$\Delta B_{\text{rd}}$’ is the reduced demand (kW), ‘$C_{\text{rd}}$’ is the cost of generation (taken as $154/kW) and ‘$I_B_{\text{rd}}$’ is the depreciation cost for generation (taken as 0.2)

(b) Benefit due to released feeder capacity

$$B_{\text{rf}} = \Delta B_{\text{rf}} \times C_{\text{rf}} \times I_B_{\text{rf}}$$

Here, ‘$\Delta B_{\text{rf}}$’ is the released feeder capacity (kVA), ‘$C_{\text{rf}}$’ is the cost of the feeder (taken as $2.64/kVA) and ‘$I_B_{\text{rf}}$’ is depreciation cost of the feeder (taken as 0.2)
(c) Benefit due to savings in energy

\[ B_{se} = \Delta B_{se} \times R \]  

Here, '\( \Delta B_{se} \)' is the savings in energy = (annual energy losses before installing the DG(s)–annual energy losses after installing DG(s)) (KWh) and 'R' is the cost of energy (taken as $ 0.1/kWh).

(d) Installation cost of DG(s)

\[ C_{dg} = P_{dg} \times C_{dg} \times IC_{dg} \]  

Here, '\( P_{dg} \)' is the total kW size of the DG(s), '\( C_{dg} \)' and '\( IC_{dg} \)' are the cost (Rs. 4200/kW) and depreciation cost (taken as 0.2) of the DG(s).

2.1.2 Minimization of Voltage Deviation (\( V_{dev} \)) (p.u.)

It is necessary to maintain the voltage magnitude at the nodes within permissible limits to increase the security of the system. For this, it is necessary to minimize the voltage deviation at system nodes. The system voltage deviation can be calculated as

\[ \text{min}(I_{dev}) = \min \left[ \sum_{j=2}^{N} \left( V_j - |V_j - V_{rated}| \right)^2 \right] \]  

where, '\( V_j \)' and '\( V_{rated} \)' are the voltage magnitude at 'j' th node after installing DG(s) and rated voltage considered to be 1.0 p.u.

2.1.3 Minimization of Section Current Index (SCI)

Providing the active and reactive power near the loads may increase or decrease the current flow in some sections of the network, thus releasing more capacity or also place out of distribution line limits. The Section Current Index (SCI) gives important information about the level of currents through the network. The section current index can be calculated when performing the power flow analysis before and after installation of DG(s)

\[ \text{min}(I_{sci}) = \min \left[ \frac{\sum_{i=1}^{n} (I_{sm} - I_{sa})}{L} \right] \]  

Where, '\( I_{sm} \)' and '\( I_{sa} \)' are the mean and line section current after placing DG(s), '\( L \)' total number of line sections.

2.2 Constraints

The following equality and in-equality constraints are considered for this problem.

2.2.1 Equality Constraints

The constraints that must be satisfied in the load flow solution with DG(s) is

\[ P_{S/S} = \sum_{i=2}^{N} P_{load}^i + \sum_{j=1}^{n} P_{lin}^j - \sum_{k=1}^{ndg} P_{dg}^k \]  

Here, '\( i \)' is the node number, '\( j \)' is the branch number and '\( k \)' is the DG(s) installed node number.

2.2.2 In-Equality Constraints

Node voltage magnitude limits

\[ V_{j,min} \leq V_j \leq V_{j,max} \quad ; \quad \forall \quad j = 2,3,\ldots,N \]  

DG(s) size limit(s)

\[ 0 \leq P_{dg,j} \leq P_{dg,j}^\max \quad ; \quad \forall \quad j = 2,3,\ldots,ndg \]  

where, '\( V_{j,min} \)' and '\( V_{j,max} \)' are the minimum and maximum voltage magnitudes (p.u) at 'j' th node and '\( P_{dg,j}^\max \)' is the maximum size(s) of DG(s) which is 80% of the total active power load of base case system.

3. Optimal Location of DG(s)

The best location to install DG(s) is identified using Loss Sensitivity Index (LSI) analysis. As the DG injects active power at the node where it is connected, hence, the LSI value at system nodes can be calculated as follows:

The active power losses in kth branch can be calculated as

\[ P_{loss}(k) = \frac{[P_{eq}(j) + Q_{eq}(j)]R(k)}{(V(j))^2} \]  

where, the sum of total active demand beyond the node 'j' can be calculated as

\[ P_{eq}(j) = \sum_{m=2}^{N} P_{load}(m) \]  

From this, the change in active power losses for a change in total demand results the loss sensitivity index, which can be expressed as
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\[ LSI(j) = \frac{\partial P_{loss}(k)}{\partial P_{eq}(j)} = \frac{2 \times P_{eq}(j) \times R(k)}{(V(j))^2} \]  

(8)

where, \( R(k) \) is the kth branch resistance.

The algorithmic steps of locating the DGs in a given radial distribution is given below

Step 1: Read the system line and load data i.e the line resistance and reactance and the active and reactive power loads at each node.

Step 2: Calculate the total active power demand beyond each node.

Step 3: At each node the active load is compensated by injecting the active power (\( P_{dg} \)) which is equal to load active power, then, solve the load flow and calculate LSI value at each node.

Step 4: Arrange these LSI values in ascending order and select the nodes from top to install DG(s).

Step 5: Stop.

To identify the optimal number of DG(s) for a given system, at first, one DG is installed in least LSI valued node and optimization problem (procedure described in section-4) is solved with Total Power Losses (TPL) as objective and while satisfying system equality and inequality constraints. This procedure is repeated with two DGs in top two locations and so on. Finally, identify the optimal number of DGs based on the TPL value.

4. Modified Cuckoo Search Algorithm

In general, the existing swarm based optimization algorithms work based on certain evolutionary operations to search the global best solution in the solution space. But, these algorithms suffer from poor convergence rate when compared to the modern hybrid algorithms. Cuckoo Search Algorithm (CSA) is a novel technique developed for solving continuous and non-linear optimization problems. This algorithm works based lifestyle of cuckoo bird, characteristics in egg lying as well as breeding.

Keeping all these points in mind, in this paper, a novel Modified Cuckoo Search Algorithm (MCSA) is developed to enhance the convergences rate and quality of the solution too. This algorithm generates array of initial population for the problem control variables uniformly rather than randomly using the following MATLAB pseudo code.

Initial population=random ('unif', min, max, N, npar)

where, ‘min’ and ‘max’ are the minimum and maximum limits of the control variables, ‘N’ is the total population number and ‘npar’ is the total number of control variables.

Because of this, the consistence of local solutions before starting iterative process occupies entire solution region. Due to this, the best populations are considered to start the iterative process.

Using this, the problem control variables, such as active power injected by the DG(s) are generated randomly for a given population number (N).

\[ U^T = [P_{DG1}, P_{DG2}, \cdots, P_{DGn}] \]

Load flow problem is solved using the methodology presented in [1]. Then, the objective function and fitness values for the respective population are evaluated. The fitness function for a population can be calculated using

\[ fit_i = \frac{1}{1 + J_i}, \quad \forall \quad i = 1, 2, \ldots, P \]

The final objective values and fitness vectors can be tabulated as

\[
\begin{bmatrix}
J_1 & fit_1 \\
J_2 & fit_2 \\
\vdots & \vdots \\
J_N & fit_N
\end{bmatrix}
\]

where, \( J_1, J_2, \ldots, J_N \) and \( fit_1, fit_2, \ldots, fit_N \) are the objective and fitness values of the respective population. This step can be considered as first stage of the proposed methodology.

In second stage of the proposed methodology, pair-wise best solution is forwarded for further process and the remaining solution is discarded under survival of the fittest. The complete process is represented as

\[
\begin{align*}
J_1 & \quad fit_1 \\
J_2 & \quad fit_2 \\
& \quad \text{if } fit_1 < fit_2 \text{ then } \rightarrow J_1, fit_1, \text{ else } \rightarrow J_2, fit_2 \\
J_3 & \quad fit_3 \\
& \quad \text{if } fit_2 < fit_3 \text{ then } \rightarrow J_2, fit_2, \text{ else } \rightarrow J_3, fit_3 \\
& \quad \vdots \\
J_{N-1} & \quad fit_{N-1} \\
J_N & \quad fit_N \\
& \quad \text{if } fit_{N-1} < fit_N \text{ then } \rightarrow J_{N-1}, fit_{N-1}, \text{ else } \rightarrow J_N, fit_N
\end{align*}
\]

Because of this, the total number of populations processed in iterative process gets reduced to 50%
and very clearly, the iterative process starts with best population and consequently, the time taken to get final best solution is less. The remaining steps of proposed method are discussed as follows:

4.1 Performing Levy Flight Operation

Levy flight is the search process of population of solution from the randomly generated initial population. After performing the levy flight operation, cuckoo chooses the host nest position randomly to lay egg is given in Eqn. (9) using Eqn. (10) for \( i \) th cuckoo, the initial population is updated using,

\[
x_{i}^{(t+1)} = x_{i}^{(t)} + s_{ab} \times \alpha \oplus \text{Levy}(\lambda)
\]

where, \( \alpha \) random number between \([-1,1]\), \( \oplus \) is entry wise multiplication, \( s_{ab} > 0 \), it is the step size, based on this only new solution is generated. Here, step size can be calculated as

\[
s_{ab} = x_{ab}^{i} - x_{fb}^{b} \quad \text{where, } a,f = 1,2,\ldots,n \; ; \; b = 1,2,\ldots,m
\]

Finally, the levy flight operator can be calculated as

\[
\text{Levy}(\lambda) = \left( \frac{\Gamma(1+\lambda) \times \sin \left( \frac{\pi \times \lambda}{2} \right)}{\Gamma(1+\lambda) \times \lambda \times 2^{\frac{\lambda-1}{2}}} \right)^{\frac{1}{\lambda}} ; 1 < \lambda \leq 3
\]

Performing Levy flight operation on initial population will generate new population and which results the solution around the best solution. Population vector is modified using levy flight equation \( x_{ab}^{t+1} \) i.e, belongs to \( a \)th nest and \( b \)th control variable. Here old value \( x_{ab}^{i} \) is updated with respect to \( f \)th neighbourthood’s nest.

4.2 Performing Crossover Operation

Recently an efficient operator i.e. crossover has been designed for searching process. This is one of the popular hybrid operations is performed on populations to increase the extended capability to increase the concentration towards best solution by taking the local best solution as reference. The population after levy flight operation are again operated using crossover operation. This can be mathematically expressed as in Eqn. (11).

\[
x_{ab}^{\text{new}} = (1 - \lambda) \times x_{ab}^{\text{ref}} + \lambda \times x_{ab}^{\text{old}}
\]

where, \( \lambda \) is the random number between \([0,1]\). Updated value \( x_{ab}^{\text{new}} \) is obtained by crossover of old value and its reference value. After crossover, check the control variable limits for all the final population. If upper limit is violated, set to the maximum value, if lower limit is violated, set to the minimum value and if it is within the limit keep as such.

After performing this operation, using new population, the load flow is performed and the objective function and fitness values are calculated. The local best solutions are updated and the global best solution is selected using selection process.

5. Multi-Objective Solution Strategy

In the conventional optimization problem, one of the system objectives (e.g., savings, Vdev, SCI, etc.) is optimized under certain system constraints. In multi-objective optimization problem, these conflicting objectives are optimized simultaneously to obtain a set of solutions, instead of one particular solution, for the given problem constraints.

To clarify this problem, consider the case in which the savings objective is maximized with increased voltage deviation, and vice-versa. For this type of problem, there are many solutions rather than a single, optimal solution, and none of these solutions are categorically ‘better’ than any other solution. In this paper, the final population after evaluating the considered objectives are performed with non-dominated sorting, crowding sorting procedures and finally the compromised solution is selected using the fuzzy decision making tool. The following are the detailed explanation regarding each procedure.

5.1 Non-Dominated Sorting Procedure

The multi-objective problem finds a set of non-dominated solutions, known as the Pareto-Front Set (PFS), which describe the priority of a solution with respect to the others. Let us consider two solutions of the system, \( \text{Sol}_1 \) and \( \text{Sol}_2 \). If \( \text{Sol}_1 \) dominates \( \text{Sol}_2 \), then \( \text{Sol}_1 \) is a non-dominated solution when the following conditions are satisfied:

\[
\forall \; m \in 1,2,\ldots,p ; \quad J_{m}(\text{Sol}_1) \leq J_{m}(\text{Sol}_2)
\]

\[
\forall \; n \in 1,2,\ldots,p ; \quad J_{n}(\text{Sol}_1) \leq J_{n}(\text{Sol}_2)
\]

where, \( \; \) is the total number of objectives. Therefore, the PFS are obtained by mapping these non-dominated solutions into the entire search space. The resulting Pareto-optimal fronts constitute the Pareto-optimal set.
These solutions are stored in a repository that is used to estimate the density of solutions around a particular solution. The distance (crowding distance) between each pair of solutions is calculated, and then the solutions are arranged based on their crowding distances, explained as follows:

5.2 Crowding Distance Calculation
Using the density of obtained solutions around a solution in PFS, then calculate the average distance between each of the two points related to the objective functions. This calculation resembles, perimeter of the cuboids formed by the nearest neighbours as the vertices. This distance, can be called as crowding distance. This operation requires, sorting of the solutions based on the objective function values in ascending order. For each of the populations, the largest and smallest objective function values are assigned as boundary values and the remaining populations are assigned a distance value equal to the absolute normalized difference in the function values of two adjacent populations.

After this, crowding distance comparison is performed between each of the two populations, based on two attributes: out of which one is non-domination rank and the other one is crowding distance. The final best PFS is selected with the populations which has lowest non-domination rank.

5.3 Fuzzy Decision Making Tool
After determining the total PFS for a given optimization sub-problem using Non-Dominated Sorting Modified Cuckoo Search Algorithm (NSMCSA), the optimal settings are selected by the decision maker. For this purpose, a fuzzy decision-making tool applies the following linear membership function to minimize the objective functions:

$$\mu_m^n = \begin{cases} 1 & J_m^* \leq \min(J_m) \\ \frac{\max(J_m) - J_m^*}{\max(J_m) - \min(J_m)} & \min(J_m) \leq J_m^* \leq \max(J_m) \\ 0 & J_m^* \geq \max(J_m) \end{cases}$$

where, $J_m^*$ and $\mu_m^n$ are the $m^{th}$ objective function in the $n^{th}$ Pareto optimal solution and its membership function, respectively. The preferred degree of the Pareto optimal solutions can be defined as Eqn. (12)

$$\mu_{opt} = \sup_{m=p} \sum_{n=1}^{N} W_n \mu_m^n$$

where, $W_i \geq 0 \sum_{i=1}^{N} W_i = 1$, $W_i$ is the weight value of the $i^{th}$ objective function. Therefore, the optimal Pareto solution and the corresponding settings are obtained by the proposed algorithm based on the adopted weight factors.

6. Implementation of the Proposed NSMCSA Algorithm
In this section, the two-stage initialization process for the multi objective optimization problem and its implementation procedures are explained. The first stage of the NSMCSA is performing the load flow and evaluating the objective functions and fitness values. In the second stage, the Pareto Front Sets (PFS) are obtained from these solutions, and the best 50% of the
Pareto fronts are retained for further consideration. Thus, the iterative process starts with the better PFSs and, as the iteration number increases, the global best PFS is obtained. The process of two-stage initialization for the multi-objective optimization problem is shown in Figure 1. This methodology was implemented on a personal computer with Intel Core2Duo processor and 2 GB RAM installed with MATLAB environment. The complete implementation procedure of the proposed NSMCSA flowchart is shown in Figure 2.

7. Results and Analysis

To show the effectiveness of the proposed methodology, standard Schaffer functions-1,2 and Zitzler-Deb Thiele's function-3, 15-node 4, 33-node 5 and 69-node 6 radial distribution systems are considered. At first, single objective optimization problem is solved using developed MCSA methodology and later multi objective optimization problems are solved using developed NSMCSA methodology.

7.1 Benchmark Systems

The multi objective results for the standard Schaffer functions are shown in Figure 3. From this figure, it is identified that, the proposed NSMCSA selects the best Pareto front from the total generated solutions and the proposed fuzzy decision approach selects the best compromised solution from the best Pareto front.
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To extend the validity of the proposed NSMCSA, the multi objective results for the Zitzler-Deb Thiele's function-3 are shown in Figure 4. From this figure, it is clear that, the proposed methodology yields better results for the multi objective optimization problem.

From these results, it is identified that, because of the effectiveness of the proposed methodology, the Pareto solutions confines the entire trade-off region. Similarly, the multi objective optimal placement of DGs problem for radial distribution systems can be solved effectively using the proposed methodology.

For each of the test systems, at first, the optimal location(s) to install DG(s) are identified using loss sensitivity index (LSI) analysis. For this, LSI values are evaluated at each of the node using the procedure and are arranged in ascending order. Then, DG is installed in least LSI valued location and the optimal DG settings and total power losses are evaluated using the optimization procedure. This process is repeated for two, three DG locations and the total power losses are evaluated. Finally, the number of locations which yields lowest power losses is considered as the optimum number of DG locations. Next, by installing DGs in these optimum locations, the savings, voltage deviation and section current index objectives are optimized in the presence of DGs individually using MCSA (section-4) and simultaneously using NSMCSA are performed. The respective results are analyzed using graphical and as well as numerical results.

7.2 Example-1 (15-Node)
The 15-node radial distribution system, with 14 branches is considered. For this system, the total demand is 1752 KVA. To identify the effect of DG on system performance, the ascending ordered LSI values at the system nodes are tabulated in Table 1. From this table, it is identified that, the top three highest LSI valued nodes are 15, 11 and 13. Among these nodes, to identify the optimum number of locations, the total power losses are optimized in the presence of DG.

| S. No | Node No | LSI value |
|-------|---------|-----------|
| 1     | 15      | 0.0005    |
| 2     | 11      | 0.0008    |
| 3     | 13      | 0.001     |
| 4     | 10      | 0.0013    |
| 5     | 14      | 0.0018    |
| 6     | 7       | 0.0019    |
| 7     | 8       | 0.0019    |
| 8     | 12      | 0.0032    |
| 9     | 4       | 0.0037    |
| 10    | 9       | 0.0048    |
| 11    | 5       | 0.005     |
| 12    | 6       | 0.0072    |
| 13    | 3       | 0.0091    |
| 14    | 2       | 0.0166    |

The optimized TPL values at optimal location(s) are tabulated in Table 2. From this table, it is observed that, minimum TPL value is obtained, if the DGs are placed at nodes 15 and 11 when compared to the other locations. From this, the further analysis is performed by placing the DGs in these locations.
Table 2. Optimum DG Locations of 15-Node RDS

| S. No | Locations | TPL value, kW |
|-------|-----------|---------------|
| 1     | 15        | 42.688        |
| 2     | 15, 11    | 30.7701       |
| 3     | 15, 11, 13| 59.110        |

The detailed summary of the test results for DG placement are tabulated in Table 3 for TPL minimization. From this table, it is observed that, 28.34 kW losses are reduced with DGs when compared to without DGs. It is also observed that, minimum voltage magnitude is obtained at node-13 because of lack of reactive support at this node.

Table 3. Summary of Test Results for DG Placement of 15-Node RDS

| Description                | Without DG | With DG |
|----------------------------|------------|---------|
| DG locations               | 15, 11     |         |
| DG size, kW                | 400 kW, 827 kW |       |
| TPL, kW                    | 59.1095    | 30.7701 |
| Loss reduction, kW         | 28.34      |         |
| Min voltage (p.u) (8th node)| 0.93911   |         |

To show the effect of DGs, the variation of voltage values and power losses are shown in Figures 5 and 6. From these figures, it is identified that, the proposed method with DGs yields better results when compared to the without DGs. The voltage magnitude at system nodes is enhanced with DGs and power flow in the branches is redistributed. Due to this, the power losses are reduced in the branches with DGs when compared to without DGs.

Table 4. Single Objective Optimized Results with DGs of 15-Node RDS

| Control Parameters | Without DG | With DGs | Voltage deviation (Vdev) (p.u.) Minimization | Section current Index (SCI) Minimization |
|--------------------|------------|----------|---------------------------------------------|----------------------------------------|
| P_{dg15}, kW       | -          | 750      | 600                                         | 450                                    |
| P_{dg11}, kW       | -          | 450      | 450                                         | 300                                    |
| KP, ($)             | -          | 36923.08 | 27692.31                                    | 23076.92                               |
| KE, ($)             | -          | 1640.29  | 1495.191                                    | 1347.95                                |
| KE, ($)             | -          | 22641.23 | 25067.08                                    | 21024                                  |
| KC, ($)             | -          | 15507.69 | 11630.77                                    | 9692.308                               |
| Savings, ($)        | -          | 45696.91 | 42623.81                                    | 35756.56                               |
| Vdev, p.u.          | 0.08784    | 0.02248  | 0.02124                                      | 0.02426                                |
| SCI value           | 0.5752     | 0.5818   | 0.58106                                      | 0.57198                                |
| TPL, kW             | 59.5954    | 29.1213  | 28.9215                                      | 29.7424                                |
The single objective optimized results with savings, Voltage Deviation (Vdev) and Section Current Index (SCI) as objectives for without and with DGs using the developed MCSA is tabulated in Table 4. From this table, it is identified that, with DG maximum benefit in terms of savings, Vdev and SCI values is obtained when compared to without DG.

To exemplify this more clearly, when savings objective is maximized, the size of the DGs is increased and results in decrease of Vdev and TPL values. This is due to the increase of benefits due to reduced demand, released feeder capacity and energy loss savings. Even though, the size and there by the cost DGs is more, the net savings is more due to the technical benefits when compared to the savings obtained when other objectives such as Vdev and SCI are considered.

Similarly, when Vdev objective is minimized, the size of the DG required is also reduced. In this case, the benefits due to reduced demand, released feeder capacity and the energy losses are reduced and there by the net savings are reduced when compared to other cases. In this case, it is noticed that, the current balance in the sections is not proper due to which the SCI value is more when compared to other objectives.

At last, the DGs size is decreased when SCI objective is minimized when compared to other objectives. Due to this, the SCI value is decreased which balances the current flow in the branches. This leads increase of voltage deviation at the system nodes. Here also, the benefits due to reduced demand, released feeder capacity and energy losses are less then, the savings are decreased.

To validate the proposed method, savings obtained with DGs is compared with the existing method and are tabulated in Table 5. From this table, it is identified that, the proposed method yields better savings than the existing method with less DG size. From this, by considering the economic factors such as savings in released feeder capacity as well as the savings in annual energy losses in the objective function, and technical factors such as the voltage deviation and section current index, the overall savings are increased.

From this entire single objective analysis, it is identified that, minimization/maximization of value of the objectives maximizes/minimizes the value of the other objectives. Hence, it is necessary to solve multi-objective optimization problem to get compromised solution among the objectives.

| Control Parameters | Existing method | Proposed method |
|--------------------|-----------------|-----------------|
| $P_{DG}$, kW       | 792 (3)         | 750 (15)        |
| $P_{DG}$, kW       | 382 (6)         | 450 (11)        |
| $KE$, ($)          | ---             | 36923.08        |
| $KF$, ($)          | ---             | 1640.29         |
| $KP$, ($)          | ---             | 22641.23        |
| $KC$, ($)          | ---             | 15507.69        |
| Savings ($), ($)   | ---             | 45696.91        |
| Vdev (p.u)         | 0.0279          | 0.02248         |
| SCI                | ---             | 0.5818          |
| Total Power Losses (kW) | 29.94 | 29.1213 |

The multi objective optimized Pareto front solutions when two and three objectives are solved in the presence of DGs using the developed NSMCSA are shown in Figures 7 to 10. From these figures, it is observed that, the generated Pareto solutions confine the entire trade-off region due to the effectiveness of the developed algorithm. It is also observed that, the developed fuzzy decision making tool selects the compromised solution from the best Pareto front solutions based on the weights assigned to the objectives.

![Figure 7](image-url) Pareto Front Solutions (Vdev-Savings) with DGs of 15-Node RDS.
Using the fuzzy decision making tool the numerical results for the two and three objectives is tabulated in Table 6. From this table, it is identified that, based on the weights assigned to the objectives, respective compromised solutions are selected from the best Pareto front solutions.

### 7.3 Example-2 (33-Node)

The 33-node radial distribution system, with 32 branches is considered. For this system, the total demand is 4369 KVA. To identify the effect of DG on system performance, the top three least LSI valued nodes are 32, 30 and 22. Among these nodes, to identify the optimum number of locations, the total power losses are optimized in the

![Figure 8. Pareto Front Solutions (SCI-Savings) with DGs of 15-Node RDS.](image1)

![Figure 9. Pareto Front Solutions (Vdev-SCI) with DGs of 15-Node RDS.](image2)

![Figure 10. Pareto Front Solutions (Savings-Vdev-SCI) with DGs of 15-Node RDS.](image3)

### Table 6. Multi Objective Optimized Results with DGs of 15-Node RDS

| W1 | W2 | W2 | Savings ($) | Vdev (p.u) | SCI value | $P_{DG15}$ (kW) | $P_{DG11}$ (kW) |
|----|----|----|-------------|------------|-----------|-----------------|-----------------|
| **TWO OBJECTIVES** | | | | | | | |
| 0.8 | 0.2 | - | 47314.14 | 0.02507 | - | 613 | 418 |
| 0.5 | 0.5 | - | 45136.78 | 0.02251 | - | 477 | 461 |
| 0.2 | 0.8 | - | 43959.65 | 0.02017 | - | 243 | 389 |
| 0.8 | - | 0.2 | 46318.84 | - | 0.6196 | 627 | 210 |
| 0.5 | - | 0.5 | 41126.94 | - | 0.5162 | 483 | 359 |
| 0.2 | - | 0.8 | 36241.95 | - | 0.4586 | 362 | 354 |
| - | 0.8 | 0.2 | - | 0.02092 | 0.5119 | 552 | 321 |
| - | 0.5 | 0.5 | - | 0.02569 | 0.4519 | 464 | 257 |
| - | 0.2 | 0.8 | - | 0.02623 | 0.4181 | 381 | 312 |
| **THREE OBJECTIVES** | | | | | | | |
| 0.8 | 0.1 | 0.1 | 46431.89 | 0.02816 | 0.5965 | 652 | 352 |
| 0.1 | 0.8 | 0.1 | 43254.18 | 0.02107 | 0.5119 | 587 | 354 |
| 0.1 | 0.1 | 0.8 | 37684.35 | 0.02462 | 0.4688 | 241 | 485 |
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presence of DG. From this analysis, it is observed that, minimum TPL value is obtained, if the DGs are placed at nodes 32 and 30 when compared to the other locations. From this, the further analysis is performed by placing the DGs in these locations.

The detailed summary of the test results for DG placement are tabulated in Table 7 for TPL minimization. From this table, it is observed that, 64.3686 kW losses are reduced with DGs when compared to without DGs. It is also observed that, minimum voltage magnitude is obtained at node-18 because of lack of reactive support at this node.

Table 7. Summary of Test Results for DG Placement of 33-Node RDS

| Description                  | With DG |
|------------------------------|---------|
| DGs location                 | 33, 18  |
| DGs size, kW                 | 1034, 191|
| TPL, kW                      | Without device 213.5642 |
|                              | With DG 76.1659 |
| Loss reduction, kW           | 137.3983 |
| Min voltage (p.u) (18th node)| 0.94287 |

From this table, it is identified that, the proposed method yields better savings than the existing method.

Table 9. Validation for Savings Objective for 33-Node RDS

| Control Parameters | Existing method | Proposed method |
|--------------------|-----------------|-----------------|
| $P_{DG1}$, kW      | 3070 (6)        | 981 (33)        |
| $P_{DG2}$, kW      | 590 (15)        | 245 (18)        |
| $K_P$, $           | 37723.08        |
| $K_F$, $           | 543.7033        |
| $K_E$, $           | 57816           |
| $K_C$, $           | 15843.69        |
| Savings ($)        | ----            | 80239.09        |
| $V_{vac}$, (p.u)   | 0.031           | 0.04381         |
| SCI                | 0.6534          |
| Total Power Losses (KW) | 51.50   | 70.56           |

The single objective optimized results with savings, voltage deviation (Vdev) and Section Current Index (SCI) as objectives for with and without DGs using the developed MCSA is tabulated in Table 8. It is identified that, with DG maximum benefit in terms of savings, Vdev and SCI values is obtained when compared to without DG. For this system also, the same inferences can be observed as in the previous system.

Further, the savings obtained with DGs using the proposed method is compared with the existing method and are tabulated in Table 9. From this table, similarly, the multi objective optimized Pareto front solutions when two and three objectives are solved using the developed NSMCSA and using the fuzzy decision making tool and the numerical results for the two and three objectives are tabulated in Table 10. From this table, it is identified that, based on the weights assigned to the objectives, respective compromised solutions are selected from the best Pareto front solutions.

7.4 Example-3 (69-Node)
The 69-node radial distribution system, with 68 branches is considered. For this system, the total demand is 4647 KVA. To identify the effect of DG on system performance, the top three least LSI valued nodes are 57, 61 and 62. Among these nodes, to identify the optimum number
of locations, the total power losses are optimized in the presence of DG. From this analysis, it is observed that, minimum TPL value is obtained, if the DGs are placed at nodes 57 and 61 when compared to the other locations. From this, the further analysis is performed by placing the DGs in these locations.

The single and multi-objective optimized results with savings, Voltage Deviation (Vdev) and Section Current Index (SCI) as objectives for with and without DGs using the developed MCSA and NSMCSA are tabulated in Table 11. From this table, it is identified that, with DG maximum benefit in terms of savings, Vdev and SCI values is obtained when compared to without DG. For this system also, the same inferences can be observed as in the previous system. It is also identified that, based on the weights assigned to the objectives, respective compromised solutions are selected from the best Pareto front solutions.

Table 10. Multi Objective Optimized Results with DGs of 33-Node RDS

| W1 | W2 | W2 | Savings ($) | Vdev (p.u) | SCI value | \( P_{\text{dg18}} \) (kW) | \( P_{\text{dg33}} \) (kW) |
|----|----|----|-------------|------------|-----------|----------------|----------------|
| TWO OBJECTIVES | 0.8 | 0.2 | - | 79422.62 | 0.04416 | - | 682 | 621 |
| | 0.5 | 0.5 | - | 78681.51 | 0.04148 | - | 582 | 510 |
| | 0.2 | 0.8 | - | 69462.35 | 0.03071 | - | 505 | 566 |
| | 0.8 | - | 0.2 | 77652.38 | - | 0.6604 | 662 | 467 |
| | 0.5 | - | 0.5 | 69127.61 | - | 0.6415 | 578 | 493 |
| | 0.2 | - | 0.8 | 60235.54 | - | 0.6355 | 525 | 614 |
| | - | 0.8 | 0.2 | 67989.82 | 0.03814 | 0.6094 | 582 | 569 |
| | - | 0.5 | 0.5 | 65416.65 | 0.04687 | 0.6557 | 537 | 697 |

Table 11. Multi Objective Optimized Results with DGs of 69-Node RDS

| W1 | W2 | W2 | Savings ($) | Vdev (p.u) | SCI value | \( P_{\text{dg18}} \) (kW) | \( P_{\text{dg61}} \) (kW) |
|----|----|----|-------------|------------|-----------|----------------|----------------|
| TWO OBJECTIVES | 0.8 | 0.2 | - | 78456.39 | 0.04989 | 0.6459 | 678 | 778 |
| | 0.5 | - | 0.8 | 68419.28 | 0.03816 | 0.6210 | 575 | 667 |
| | 0.2 | 0.5 | - | 55252.22 | 0.02289 | 0.6288 | 467 | 385 |
| | - | 0.2 | 0.8 | 64913.2 | 0.02962 | 0.6357 | 489 | 324 |

8. Conclusion

In this paper, a novel optimization solution methodology based on modified cuckoo search algorithm has been proposed with system savings, voltage deviation and SCI as objectives. The optimal location(s) identification methodology for DG(s) in a given system based on TPL and LSI values has been presented. With this, the economic and as well as technical aspects of the given distribution system has been analyzed in the presence of DG(s). From the analytical results, it has been concluded that, the locations obtained using the proposed methodology yields better results when compared to the existing literature methods. Finally, the more realistic multi objective optimization problem has been solved using the proposed methodology based on non-dominated sorting and fuzzy decision approaches while satisfying system equality and in-equality constraints.
The presented methodology has been tested on 15-node, 33-node and 69-node radial distribution systems with supporting validations of numerical and graphical results.

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