© July 2024 | IJIRT | Volume 11 Issue 2 | ISSN: 2349-6002

Distribution Network Reconfiguration for power loss minimization using Sequential Learning Neural Network

A.S. Chaitra[1], Dr.H.R. Sudarshana Reddy[2], Dr.A. Manjunatha[3], Dr.M.S. Nagaraja[4]
[1]*Assistant Professor, Department of Electronics and Communication Engineering, Sri Krishna Institute of Technology, Bangalore*
[2]*Regional Director, Visvesvaraya Technological University, Regional Office, Bangalore*
[3]*Professor, Department of Electronics and Communication Engineering, Sri Krishna Institute of Technology, Bangalore*
[4]*Prof and Head, Department of Electrical and Electronics Engineering department, BIET, Davangere*

Abstract - To supply reliable and secure power to the consumers in developing countries like India, where electrical power demand had grown up unexpectedly & unpredictably is a challenging task. Power loss minimization and voltage instability has become a major concern in many power distribution networks and many blackouts had been reported. In India, 13-18% of total power generated is lost in distribution system as losses.Also in the current scenario, considering the installation cost of 1MW generating capacity unit in India, the power loss minimization has gained huge importance, and have fascinated many researchers working in power systems. From past three decades, numerous researches had been carried out for power loss minimization and voltage profile enhancement in distribution systems.Therefore this research investigates the distribution system operations and aims to propose new techniques for improved power loss minimization and voltage profile enhancement. The objective of this study is to develop Sequential Learning Neural Network (SLNN) for solving the distributed generation placement problem, the distribution network reconfiguration problem, the capacitor placement problem, and the problem of a combination of the three. The simulated results are encouraging and demonstrate well the effectiveness of the proposed techniques. The simulated results are also compared with the results of other methods available in the literature. It is observed that the performance of proposed technique is better than the other classical techniques in terms of quality of solutions.

Key words: Network Reconfiguration, SLNN, Distribution Network, DG Replacement

I. INTRODUCTION

Radial distribution network (RDN) plays a crucial role in the power systems, responsible for power supply from the transmission systems to the customer. However, the continuously growing load has posed challenges for power companies to perate RDN efficiently and reliably. Power loss significantly affects the operating efficiency of RDNs. Hence, it is imperative to reduce power loss for RDNs to operate efficiently and economically. In this regard, many approaches have been implemented to minimize the power losses of RDNs. Network reconfiguration (NR) and distributed generation (DG) integration are two prominent techniques that attract much attention due to the development context of power sources and investment costs. NR is an effective method to minimize power loss in RDNs. RDNs are operated in the radial topology to decrease the fault level and protect coordination effectively. Tie-line switches (normally opened) and sectionalizing switches (normally closed) are two types of switches in RDNs. NR leads to a new network topology by altering the opened/closed status of switches while maintaining the radial topology of the system. NR is a vital grid strategy that decreases active power losses, improves voltage profile and system reliability [1].

Moreover, NR can transfer load from one branch to another to avoid overloading. Recently, distributed generations (DGs) have been swiftly integrated into RDNs due to electricity deregulation, fossil fuel depletion, and environmental concerns. Apart from NR implementation, the deployment of DG units is also a well-known grid strategy to decrease power losses and boost the voltage profile of RDNs. Therefore, the NR application in RDNs should be studied in the presence of DGs. Since the NR problem was firstly introduced by Merlin and Back [2], a large amount of research has also been done on the NR problem using various approaches from heuristic approaches like branch-and-bound method [2], modified branch exchange method [3], and switch exchange method [4] to metaheuristic approaches like particle swarm optimization (PSO) [5], [6], genetic algorithm (GA) [7], biased random key GA (BRKGA) [8], harmony search algorithm (HSA) [9], heuristic rules-based fuzzy multiple objectives [10], fireworks algorithm (FWA) [11], GA with varying population (GAVP) [12], and cuckoo search algorithm (CSA) [13]. In general, heuristic methods are characterized by fast convergence, but they lack the ability to handle largescale systems with many constraints. Meanwhile, metaheuristic methods have robust searchability to discover optimal solutions or near-optimal solutions, which are well suited for large-scale networks. Hence, the applications of metaheuristic methods to NR problems are constantly evolving. Recently, many researchers have applied several artificial intelligence and analytical methods to solve the optimal DGs allocation problem in RDNs.

In [14], comprehensive analytical expressions were suggested to define the allocation of PV units for maximizing the technical benefits in RDN. The objective functions include active and reactive power losses, voltage stability index, line congestion margin and voltage deviations. Mahmoud and Lehtonen [15] proposed generic closed-form analytical expressions to determine optimal locations and sizes of multi-type DGs and capacitors for optimizing reactive power loss in RDNs. Moreover, the proposed method incorporated an optimal power flow (OPF) algorithm to consider the constraints of systems. In [16], the authors utilized an efficient analytical (EA) method to obtain an optimal mix of different DG types with various generation capabilities to minimize power losses in RDNs. Researchers have constantly proposed new methods to achieve better performance for RDNs. One of those efforts is the simultaneous integration of NR and optimal DGs placement. Recent studies on the integration of these two effective strategies have been done using metaheuristic methods. Shaheen et al. [17] developed an improved equilibrium optimization algorithm (IEOA) to deal with the optimal integration of NR with DGs. Different load conditions of 33- and 69-bus systems were utilized to test the IEOA method, and its superiority was confirmed. Onlam et al. [18] applied the adaptive shuffled frogs leaping algorithm to acquire optimal NR and DGs settings on several circumstances of 33- and 69-bus RDNs to minimize system losses and enhance voltage profile.

Murty and Kumar [19] suggested NR and optimal renewable-based DGs placement considering load uncertainties. A hybrid fuzzy-bees approach was developed by Tolabi et al. [20] for NR with DG placement for reducing power losses, improving the feeder load balancing and voltage profile. In [21], an artificial bee colony was combined with a hybrid method of HSA and PSO to deal with the combined problem of NR with shunt capacitors and DGs allocation to optimize the power loss. In [22], a fuzzy multi-objective technique was utilized for handling NR. Afterwards, a heuristic approach was applied to obtain the optimal NR, which generated a solution based on the initial NR. In [23], an improved plant growth simulation method was proposed for NR with DGs presence for power loss reduction. Optimal DG locations were defined using sensitivity analysis. Bayat et al. [24] developed a heuristic approach for NR and DGs allocation to maximize loss reduction. In [25], levy flights embedded in sine–cosine algorithm to deal with NR and DGs allocation in 33-bus and 69-bus RDNs. The proposed problem considered power losses and voltage stability index objectives.

Some other typical metaheuristic methods have also been applied to handle the combination of NR and DGs allocation, such as HSA [26], adaptive CSA [27], FWA [28], big-bang crunch algorithm [29], [30], hybrid grey wolf optimizer and PSO (GWO-PSO) [31], electromagnetism-like mechanism (ELM) [32], firefly (FF) [33], and three-dimensional group search optimization (3D-GSO) [34]. Based on the aforesaid literature survey, applying the metaheuristic algorithms to the integration of NR with DGs placement has several certain limitations. Most of the previous studies only focused on small- and medium-scale RDNs without considering large-scale RDNs. Moreover, integration of NR and DGs placement is a combined optimization problem, which poses a challenge to achieve optimal solutions due to its complexity. Therefore in this work use sequential learning based neural network method to overcome the issues of previous systems.

II. PROPOSED METHODOLOGY

In the context of large-scale grid connection of distributed energy, during the reconfiguration of the distribution network, the availability of distributed energy and the load of the distribution system may be inconsistent with the prediction due to the influence of environmental factors and human factors. If the distribution network reconfiguration is still carried out according to the expected offline optimization scheme, there may be reliability problems of voltage over-limits and economic problems of increased network loss in the actual reconfiguration process. Therefore, the reconfiguration plan formulated in advance can give some guidance to the dispatch operator, but it may not be directly used in the actual reconfiguration process. This work proposes a sequential learning neural network approach to solving the electric distribution network reconfiguration. Based on the uncertainty of distributed energy output and network load in the distribution network, the online algorithm of distribution network reconfiguration realizes the second-level solution of distribution network reconfiguration, through day-ahead training of the neural network.

2.1 Problem Formulation

By rearranging the distribution system, this section aims to decrease power losses. The following equation expresses the reconfiguration's goal function.

$$M \in: P_{loss} = \sum_{i}^{Nbr} R_i \frac{P_i^2 + Q_i^2}{V_i^2}$$

Where

N_{br} = Total Number of Branches

R_i = Resistance Value of Branch

V_i = Voltage at the i^{th} branch

P_i = Active Power at i^{th} branch

Q_i = Reactive power at i^{th} branch.

2.2 Voltage Constraint: As seen in the equation below, the load bus voltages are limited by their lowest and maximum values.

$$V_{i,min} \leq V_i \leq V_{i,max}$$

Where

$V_{i,max}$ = (1.1 pu)

$V_{i,min}$ = (0.9 pu)

2.3 Current Constraint: The lower and higher limits of line currents are as follows:

$$I_i \leq I_{i,max}$$

Where

Ii and $I_{i,max}$ = current and the maximum current of i^{th} branch, respectively

2.4 Radial Topology Constraint: There must be no isolated nodes in distribution systems, and the system's architecture must be radial. The radial topology constraint looks like this:

$$N_{node} - N_{br} = 1$$

Where

N_{node} = number of nodes in the system

2.5 Working Function of Sequential Learning Neural Network

A recently proposed artificial-intelligence-based approach for handling complicated nonlinear combinatorial optimization issues is Sequential Learning Neural Network (SLNN). The SLNN technique divides the solution of the network reconfiguration problem into three parts.

2.6 Propsoed Sequential Learning Neural Network

Determining the various parameters associated with neural networks is not straight forward and finding the optimal configuration is a time and memory-consuming process. To reduce the time and memory, the SLNN algorithm is used with sequential learning. Since SLNN has a single hidden layer, the memory utilization will be less. Sequential learning is employed to reduce the memory space and also reduce the computation complexity. In sequential learning, the new hidden neurons will be added only if they impact the output determination. Also, the less contributed neuron will be removed. The parameters on the distribution network are used to train the SLNN. The architecture of the Sequential learning Neural Network is shown in Figure 1.

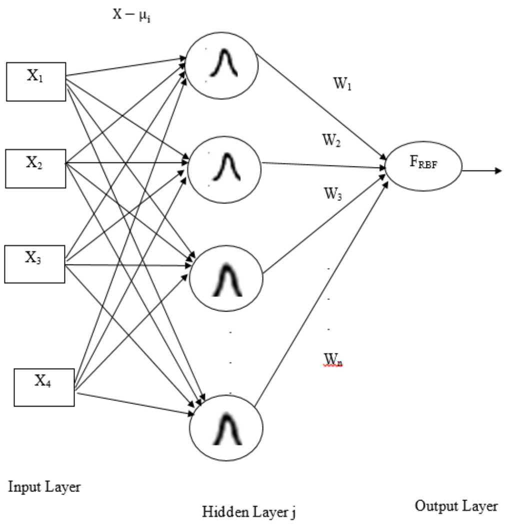

Fig. 1. Architecture of SLNN

The structure of SLNN is the same as that of Radial Bias Function (RBF) networks. Each hidden unit in the network has two parameters called a center (X_j) and a width (σ_j) associated with it. The activation function of the hidden units is Gaussian function and it is radially symmetric in the input space. Each hidden unit's output depends only on the radial distance between the input vector X_i and the center parameter C_i for that hidden unit. Each hidden unit's response is scaled by its connecting weights W_j to the output units and then summed to produce the overall network output. The following Equations calculate the overall network output.

$F_{RBF} = \sum_j W_j \varphi_j$, $j =$ 1 to n (number of hidden units)(1)

$\varphi_j = e^{-|X_j - C_i|^2} / 2\sigma_j^2$(2)

Where

φ_j =Response of the j^{th} hidden unit

W_j = Weight Connecting hidden unit j to output unit

X_j =Center of j^{th} hidden unit

σ_j = width of j^{th} hidden unit

2.7 Algorithm of SLNN

Step 1: Center Value is calculated using K-Means Clustering (discussed in following section)

Step 2: The width value is calculated using the P-Nearest neighbor method (discussed in following section)

Step 3: The RBF activation function φ_j is calculated for the training inputs using Equation (2)

Step4: Sequential learning is applied as follows

4.1 Initially, no hidden neuron exists

4.2 initialization has been done with the following values n= 0, K=0 and h=1

Where

n = number of input patterns (500)

K = Number of hidden neurons (max of 10)

h = learning cycle

4.3 For each observation (X_n, y_n),the overall network output is calculated using Equation 1

4.4 The novelty of the data is verified using the variables e_n and β_{max} . They are calculated as follows

$$e_n = y_n - F_{RBF} \vee (3)$$

$$\beta_{max} = Max(\varphi_i)(4)$$

If e_n>0.1 and $\beta_{max} < 0.6$ and K <=10

A new hidden unit is added (K=K+1)

Else

The weight updation is done for all the hidden units as follows

$$W_j(new) = W_j(old) + \alpha * \varphi_j(5)$$

Where

α = learning Rate Constant (0.1)

4.4 If all the training patterns are presented, then the number of learning cycle is incremented (h=h+1) and criteria for removing hidden units is verified

$$\theta_i = \left[\sum_{n=1}^{N} \varphi_j (x_n)\right] < 0.1 \quad (6)$$

If the above condition is satisfied, the hidden unit corresponding to this activation function contributes to the output. So it will be removed.

Step 5: If the network indicates Root Mean squared error value is close to zero, the network is converged. Else it repeated from step 4.3

2.8 K-means clustering center selection

K-Means is an unsupervised learning algorithm that solves the well-known clustering problem. K-means procedure is a simple and easy way to classify a given data through a certain number of clusters (assuming k clusters). The main idea is to define the center of k, one for each cluster. This algorithm aims at minimizing an objective function known as the squared error function which is given by

$$J(V) = \sum_{i=1}^{C} \sum_{j=1}^{C_i} (|x_i - C_j|)^2 \ (7)$$

Where

$\vee x_i - V_j \vee$ = Euclidean distance between x_i and V_j.

C = number of cluster centers

C_i = number of data points in i^{th} cluster

The algorithm of K-means clustering as follows

2.9 K-Means Clustering Algorithm

Let X = {X_1, X_2, X_3… Xn} be the set of data points and C = {C_1, C_2, C_3…C_n} be the set of centers.

Step1: The *'c'* cluster centers are randomly selected

Step2: From each datapoint and cluster center, the distance has been calculated.

Step3: The data point is selected whose distance from the cluster center is the smallest of all cluster centers

Step4: The new cluster center is recalculated using the following Equation

$$V_i = \left(\frac{1}{C_i}\right) \sum_{j=1}^{C_i} x_i \ (8)$$

Step5:The distance within each data point is recalculated and the new cluster centers are obtained.

Step6: If no data point is reassigned, then the clustering process is stopped. Else from step 3 is repeated.

3.0 Determination of Width Parameters

The next step is the determination of the width parameter of the basis functions σ_j. In this research**, the** Probabilistic -Nearest Neighbor (P-Nearest Neighbor) heuristic method is used to find the widths. Consider a given vector X_j(j=1,..C) and assume $X_{j1}, X_{j2}, \ldots X_{jP}$($1 <= j_1, j_2, \ldots j_P <= C$) are the P-Nearest neighboringcenters. The width of the basis function σ_j is given by the RMS distance of the given cluster center$X_j$to the P-nearest neighboringcenters

$$\sigma_j = \sqrt{\left(\left(\frac{1}{P} \sum_{i=1}^{P} |X_j - X_{jP}|^2\right)\right)}(9)$$

Where the X_j are the p-nearest neighbors to the centroid X_{jp}. This ensures that the basis functions overlap to some degree and hence a relatively smooth representation of the distribution is obtained. Furthermore, the entire process is elucidated through a flowchart in Figure 2, outlining the comprehensive process.

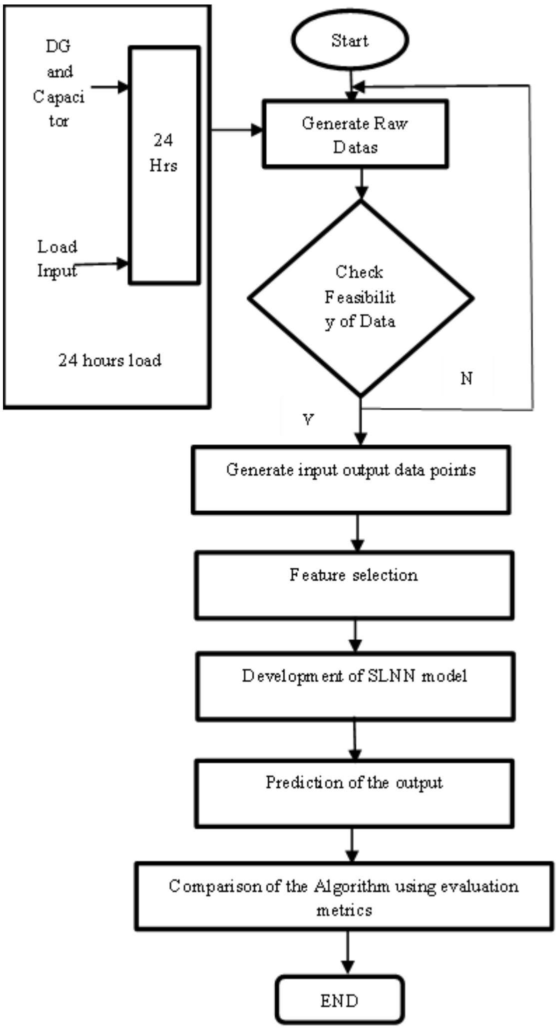

Fig. 2. Flow chart of proposed system

Comparative Analysis

This section discusses the comparative analysis results of different optimization methods. The impact of DG placement on active power loss index (APLI) and reactive power loss index (RPLI) can be assessed using following formulas. Optimal DG placement should result in higher loss indices.

$$APLI = \frac{P_{Loss} - P_{LOss}^{DG}}{P_{Loss}} \times 100 \quad (10)$$

$$RPLI = \frac{Q_{Loss} - Q_{LOss}^{DG}}{Q_{Loss}} \times 100 \quad (11)$$

The Voltage stability index (VSI) gives the relative distance from the current operating point to the point of voltage collapse. Higher values of VSI ensure that the system is capable of carrying more loading without losing its stability. The VSI can be represented by as follows

$$VSI = \lambda_{critical} - \lambda_k \quad (12)$$

Here, λ_k is the reference loading, which is assumed to be zero. $VSI\lambda_{critical}$ is the loading at the point of voltage instability.The following tables discuss the numerical result analysis for different working conditions.

The objective of the candidate load buses is to reduce the search space in the optimization procedure. Consider 2 nodes connected by a branch as apart in a radial distribution system shown in Fig.3, where the buses p and q are the sending and receiving end buses, respectively.

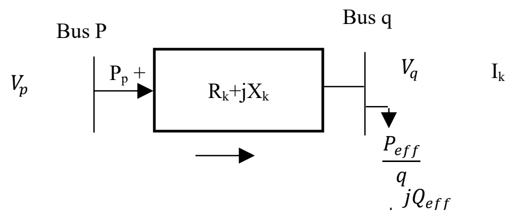

Fig. 2. Representation of two nodes in a distribution system

The active power loss index (APLI) and reactive power loss index (RPLI)flows through a branch k from node p to node q can be calculated as

$$APLI = \frac{P_{eff}}{q} + P_{LOSSk} \quad (13)$$

$$RPLI = \frac{Q_{eff}}{q} + Q_{LOSSk} \quad (14)$$

Where, APLI and RPLI are the power flows through branch k, P_{eff}/q and Q_{eff}/q are the total effective active and reactive power loads beyond the node q, respectively. P_{Lossk} and Q_{Lossk} are the active and reactive power losses through branch k, respectively. The current flowing through branch k from the node p to the node q can be calculated as:

$$I_k = \frac{V_p < \delta_p - V_q < \delta_q}{R_k + jX_k} \quad (15)$$

$$VSI = I_k * (R_k + jX_k) \quad (16)$$

Where, Vp and Vq are the voltage magnitudes at nodes p and q, respectively. δp and δq are the voltage angles at nodes p and q, respectively. Rk and Xk are the resistance and reactance of branch k, respectively. The reliability of the system is given as

$$Reliability(R) = 1 - \frac{ENS}{PD} \quad (17)$$

Where

R = Reliability

ENS = Energy Not supplied

PD = Total power demand.

The ENS to the customers can be given as [30]

$$ENS = \alpha d \sum_{k=1}^{N_{br}} \lambda_k |I_{kp}| \times V_{rated} \quad (18)$$

Where

I_{kp} = Peak Load Branch Current

R_k = Resistance

X_k = Reactance

l_k = Failure Rate for k^{th} Branch or line

V_{rated} = Rated Voltage of The System.

α = Load Factor

d = Repair Duration

III. SIMULATION RESULTS AND DISCUSSION

The IEEE 33 bus test system and a time-varying load are used to evaluate the efficacy of the recommended method. The power quality will be lowered if there is a large share of DG capacity. Here, a maximum of five DGs with a capacity of 200kW each are examined. In addition, a maximum of 10 capacitors are taken into account. In the simulation parameters and load curve, the reactive loads are calculated using the equation Q=P*tan*(cos $^{-1}$Φ), with the power factor of the load set at 0.85, in the simulation parameters and load curve. Figure 4 depicts the schematic diagram for the IEEE-33 bus test system [Chidanandappa et al 2015].

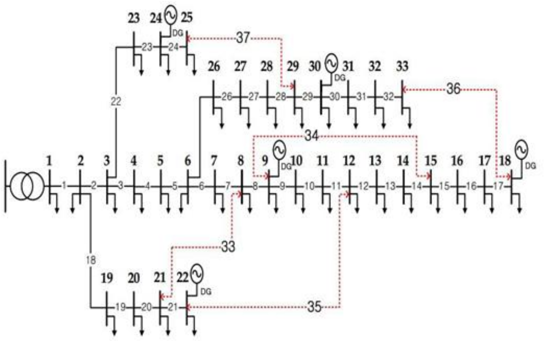

Fig. 4. IEEE 33 Bus Line Diagram

Table .1. Capacity and Simulation Parameters

Bus Specification	
System Supply Voltage	11kV
Switches in Tie Line	33 - 38
Capacity of DG	200kW Each
Capacitor Capacity	[300 600 900 1200 1500 1800 2100 2400 2700 3000]kVAR
Type of Customer	
Residential	Bus Number: 1 to 18
Industrial	Bus Number: 19 to 22
Commercial	Bus Number: 23 to 25
Educational Institution	Bus Number: 26 to 33

Table 1 displays the simulation parameters and four types of loads: residential, industrial, commercial, and school. The load hours are separated into four groups, each of which contains roughly comparable load patterns over a set length of time.

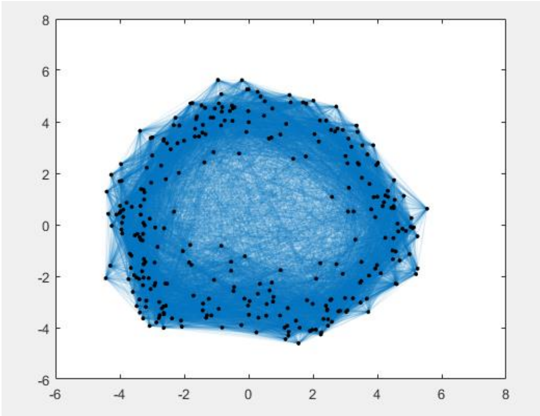

Fig. 5. SLNN Network Structure

The SLNN Simulation Network structure is shown in figure 5.The exponential decaying of the distance criterion allows fewer basis functions with large widths. With an increasing number of observations, more basis functions with smaller widths are allocated to fine-tune the approximation

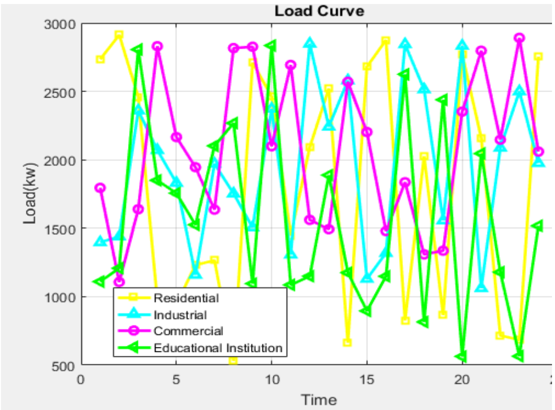

Fig. 6.Load Curve of proposed system

Figure 6 shows the simulation results of load curve response for different types (Residential, Industrial, Commercial and Educational Institute) of the customer. The performance of the proposed SLNN approach is evaluated using the following cases.

Case 1: Simultaneous Capacitor and DG Placement

Case 2: Simultaneous Reconfiguration and DG Placement

Case 3: Simultaneous Reconfiguration and Capacitor Placement

Case 4: Simultaneous Reconfiguration, DG and Capacitor Placement

CASE 1: Simultaneous Capacitor and DG Placement

Table. 2. Comparison of Base Case with Simultaneous Capacitor and DG Placement

Parameters	Base Case	Simultaneous Capacitor and DG Placement –SLNN
Tie Switch Number	33 34 35 36 37	2 5 11 33 30
Voltage range in Minimum (p.u)	0.35895	0.94
Voltage range in Maximum (p.u)	1	1
DG Location	Nil	8 31 33 4 26
DG Size(kW)	Nil	732 845 380 749 966
Capacitor Location	Nil	2 9 14 20 33 11 28 4 15 29
Capacitor Size(kVAr)	Nil	300 600 1200 1500 2100 3000 2700 1800 2400 900
Active Power Loss(kW)	26975.7017	2231.17
Reactive Power Loss(kVAr)	18145.373	1310.72
Computation Time (Sec)	0.7139	0.3897

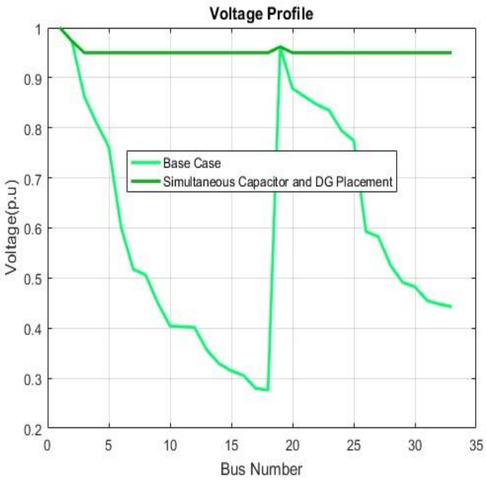

Fig. 7. Simultaneous Capacitor and DG Placement

Table 2 discuss the performance analysis of Simultaneous Capacitors and DG Placement using the SLNN method with the base case of the IEEE 33 bus system. When compared to the base situation, SLNN-based Simultaneous Capacitor and DG Placement deliver good results. The active power loss in the base scenario is 26975.7017kw and the reactive power loss is 18145.373kVAR, however the active power loss is 2231.17kW and the reactive power loss is 1310.72kVAR when employing GA based Simultaneous Capacitor and DG Placement. Figure 7 shows the voltage profile of per unit in proposed simultaneous capacitor and DG placement system.

CASE 2: Simultaneous Reconfiguration and DG Placement

Table. 3. Comparison of Base Case with Simultaneous Reconfiguration and DG Placement

Parameters	Base Case	Simultaneous Reconfiguration and DG Placement -SLNN
Tie Switch Number	33 34 35 36 37	11 20 28 31 8
Voltage range in Minimum (p.u)	0.35895	0.948
Voltage range in Maximum (p.u)	1	1
DG Location	Nil	25 18 4 33 17
DG Size(kW)	Nil	989 716 722 830 891
Capacitor Location	Nil	Nil
Capacitor Size(kVAr)	Nil	Nil
Active Power Loss(kW)	26975.7017	2224.89
Reactive Power Loss(kVAr)	18145.373	1304.02
Computation Time (Sec)	0.7139	0.332

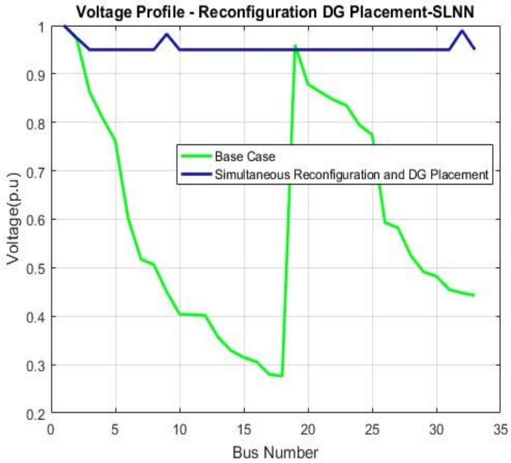

Fig. 8. Simultaneous Reconfiguration and DG Placement

Table 3 discuss the performance analysis of Simultaneous Reconfiguration and DG Placement using the SLNN method with the base case of the IEEE 33 bus system. When compared to the base situation, SLNN-based Simultaneous Reconfiguration and DG Placement deliver good results. The active power loss in the basic scenario is 26975.7017kW and the reactive power loss is 18145.373kVAR, however the active power loss is 2224.89kW and the reactive power loss is 1304.02kVAR when employing SLNN based Simultaneous Reconfiguration and DG Placement. Figure 8 shows the voltage profile of per unit in proposed Simultaneous Reconfiguration and DG Placement system.

CASE 3: Simultaneous Reconfiguration and Capacitor Placement

Table. 4. Comparison of Base Case with Simultaneous Reconfiguration and Capacitor Placement

Parameters	Base Case	Simultaneous Reconfiguration and Capacitor Placement -SLNN
Tie Switch Number	33 34 35 36 37	14 4 10 28 22
Voltage range in Minimum (p.u)	0.35895	0.97
Voltage range in Maximum (p.u)	1	1
DG Location	Nil	Nil
DG Size(kW)	Nil	Nil
Capacitor Location	Nil	14 15 19 27 29 33 4 13 30 16
Capacitor Size(kVAr)	Nil	2100 1200 600 3000 1500 2400 3000 3000 300 2100
Active Power Loss(kW)	26975.7017	2208.72
Reactive Power Loss(kVAr)	18145.373	1288.7
Computation Time (Sec)	0.7139	0.319

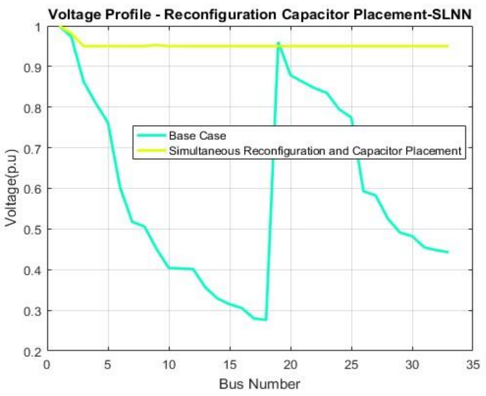

Fig. 9. Simultaneous Reconfiguration and Capacitor Placement

Table 4 discuss the performance analysis of Simultaneous Reconfiguration and Capacitor Placement using the SLNN method with the base case of the IEEE 33 bus system. When compared to the base situation, SLNN-based Simultaneous Reconfiguration and Capacitor Placement deliver good results. The active power loss in the basic scenario is 26975.7017kW and the reactive power loss is 18145.373kVAR. However, the active power loss is 2208.072kW and the reactive power loss is 1288.7kVAR when employing SLNN-based Simultaneous Reconfiguration and Capacitor Placement. Figure 9 shows the voltage profile of per unit in proposed Simultaneous Reconfiguration and Capacitor Placement system.

CASE 4: Simultaneous Reconfiguration, DG and Capacitor Placement

Table. 5. Comparison of Base Case with Simultaneous Reconfiguration, DG and Capacitor Placement

Parameters	Base Case	Simultaneous Reconfiguration, DG and Capacitor Placement - SLNN
Tie Switch Number	33 34 35 36 37	32 5 33 11 23
Voltage range in Minimum (p.u)	0.35895	0.986
Voltage range in Maximum (p.u)	1	1
DG Location	Nil	14 33 21 24 18
DG Size(kW)	Nil	895 260 591 700 181
Capacitor Location	Nil	2 4 13 27 33 9 3 29 5 20
Capacitor Size(kVAr)	Nil	300 2100 2400 3000 2700 1200 900 1800 600 1500
Active Power Loss(kW)	26975.7017	2198.89
Reactive Power Loss(kVAr)	18145.373	1249.2
Computation Time (Sec)	0.7139	0.287

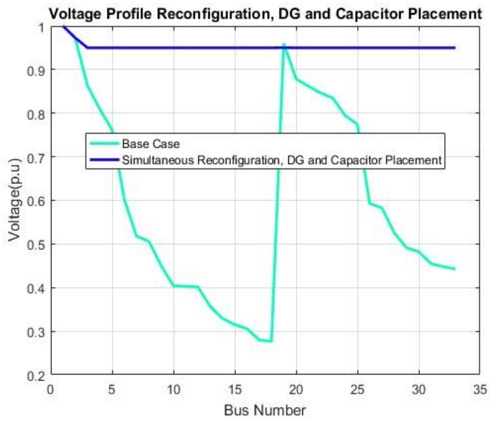

Fig. 10. Voltage profile Simultaneous Reconfiguration, DG and Capacitor Placement

Table 5 discuss the performance analysis of Simultaneous Reconfiguration, DG and Capacitor Placement using the SLNN method with the base case of the IEEE 33 bus system. When compared to the base situation, SLNN-based Simultaneous Reconfiguration, DG and Capacitor Placement deliver good results. The active power loss in the base scenario is 26975.7017kw and the reactive power loss is 18145.373kVAR. However the active power loss is 2198.89kW and the reactive power loss is 1249.20kVAR when employing SLNN-based Simultaneous Reconfiguration, DG, and Capacitor

Placement. Figure 10 shows the voltage profile of per unit in proposed Simultaneous Reconfiguration, DG and Capacitor Placement system.

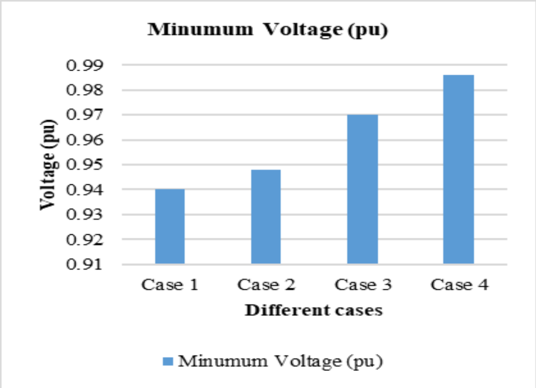

Fig. 11. Minimum voltage analysis for the different cases using SLNN

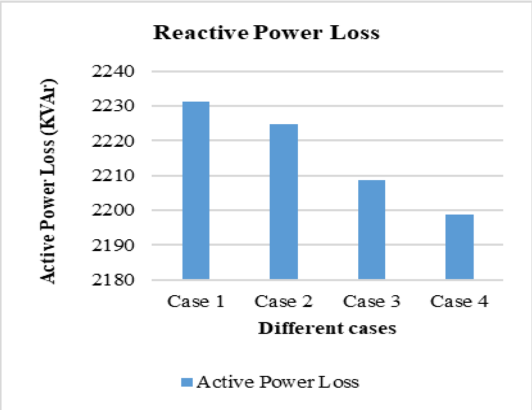

Fig. 12. Active Power analysis for the different cases using SLNN

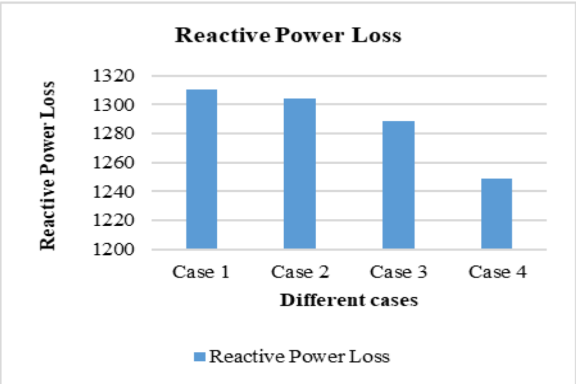

Fig. 13. Reactive Power analysis for the different cases using SLNN

Minimum voltage, active and reactive power loss analysis for the different working cases using SLNN is discussed by figures 11-13. In this analysis shwos propsoed SLNN obtianed good results

Table. 6: Fitness Function Of IEEE 33 BUS RDS For All Cases

CASES	APLI	VolDI	RPLI	RL in %	FITNESS FUNCTION
Case-1	0.81	0.063	0.81	97.01	0.878
Case-2	0.327	0.0310	0.4178	97.89	0.578
Case-3	0.319	0.0286	0.487	98.01	0.679
Case-4	0.248	0.0192	0.378	99.02	0.680

The table 6 discuss the performance analysis of APLI, VolDI, RPLI, fitness function and reliability in proposed system. In this comparison clearly shows the proposed system reliability is increased at 97.02% in case 4.

Table 7. Power Loss analysis

Existing/Proposed work	Optimization Method	Power Loss(kw)
Alam et.al [27]	MINLP	72.95
Prakash et.al [28]	PSO	74.09
Ready et.al [29]	PSO	148.30
et.al [30]	PSO	43.36
Proposed Method	SLNN	9.6

In the comparison table 7, literature [35], [36], [37] and [38] presented optimal DG placement using MINLP Technique and PSO Technique of the IEEE 33-bus RDS respectively. As compared with conventional methods the proposed SLNN have low power loss. Total power loss in all the feeder sections, PTLoss, can be found by adding up the losses in all line sections of the network. The power loss of a line section connecting buses between k and k + 1 after the reconfiguration of network is calculated as

$$PT_{LOSS} = \sum_{k=1}^{N} P_{LOSS}(k, K+1)) \quad (19)$$

IV. CONCLUSION

In this research work, a Sequential Learing Neural Network (SLNN) method is proposed for the network reconfiguration of a distribution network. This work presents the three objective functions: active power loss, DG installation cost, and closeness for the optimal network reconfiguration. The The conflicting nature of these objectives makes them best suitable for prosoed method. Training-sets for the SLNN are generated by varying the constant P-Q load models and carrying out the off-line network reconfiguration simulations. The developed SLNN model is based on the multilayer perceptron network and training is done by the back propagation algorithm. The trained SLNN models determine the optimum switching status of the dynamic switches along the feeders of the network, which thereby reduce real power loss by network reconfiguration The DG allocation is done by the sensitivity analysis of the buses which fulfill the power flow control demand in case of higher loading at the network. The proposed SLNN method is compared with the MINLP and PSO method. The SLNN results provided better tools for effective network reconfiguration. Comprehensive numerical validation is performed on standard IEEE 33 Bus system which presents that the proposed algorithm are better suited for practical application and draws better convergence characteristics.

REFERENCE

[1] Ameli, A. Ahmadifar, M.-H. Shariatkhah, and M. Vakilian, "A dynamic method for feeder reconfiguration and capacitor switching in smart distribution systems," Int. J. Elect. Power Energy Syst., vol. 85, pp. 200–211, Feb. 2017, doi: 10.1016/j.ijepes.2016.09.008

[2] Merlin, "Search for a minimal-loss operating spanning tree configuration for an urban power distribution system," in Proc. Power Syst. Comput. Conf., vol. 1, 1975, pp. 1–18.

[3] S. Ghasemi and J. Moshtagh, "A novel codification and modified heuristic approaches for optimal reconfiguration of distribution networks considering losses cost and cost benefit from voltage profile improvement," Appl. Soft Comput., vol. 25, pp. 360–368, Dec. 2014, doi: 10.1016/j.asoc.2014.08.068.

[4] D. Shirmohammadi and H. W. Hong, "Reconfiguration of electric distribution networks for resistive line losses reduction," IEEE Trans. Power Syst., vol. 4, no. 1, pp. 1492–1498, Apr. 1989, doi: 10.1109/61.25637.

[5] Y. Abdelaziz, F. M. Mohammed, S. F. Mekhamer, and M. A. L. Badr, "Distribution systems reconfiguration using a modified particle swarm optimization algorithm," Electr. Power Syst. Res., vol. 79, no. 11, pp. 1521–1530, Nov. 2009, doi: 10.1016/j.epsr.2009.05.004.

[6] M. Othman, A. A. El-Fergany, and A. Y. Abdelaziz, "Optimal reconfiguration comprising voltage stability aspect using enhanced binary particle swarm optimization algorithm," Electr. Power Compon. Syst., vol. 43, no. 14, pp. 1656–1666, Aug. 2015, doi: 10.1080/15325008.2015.1041623.

[7] J. Z. Zhu, "Optimal reconfiguration of electrical distribution network using the refined genetic algorithm," Electr. Power Syst. Res., vol. 62, no. 1, pp. 37–42, May 2002, doi: 10.1016/S0378-7796(02)00041-X.

[8] H. de Faria, M. G. Resende, and D. Ernst, "A biased random key genetic algorithm applied to the electric distribution network reconfiguration problem," J. Heuristics, vol. 23, no. 6, pp. 533–550, 2017, doi: 10.1007/s10732-017-9355-8.

[9] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. Rao, "Optimal network reconfiguration of large-scale distribution system using harmony search algorithm," IEEE Trans. Power Syst., vol. 26, no. 3, pp. 1080–1088, Aug. 2011, doi: 10.1109/TPWRS.2010.2076839.

[10] D. Das, "A fuzzy multiobjective approach for network reconfiguration of distribution systems," IEEE Trans. Power Del., vol. 21, no. 1, pp. 202–209, Jan. 2006, doi: 10.1109/TPWRD.2005.852335.

[11] M. Imran and M. Kowsalya, "A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using fireworks algorithm," Int. J. Elect. Power Energy Syst., vol. 62, pp. 312–322, Nov. 2014, doi: 10.1016/j.ijepes.2014.04.034.

[12] M. Abdelaziz, "Distribution network reconfiguration using a genetic algorithm with varying population size," Electr. Power Syst. Res., vol. 142, pp. 9–11, Jan. 2017, doi: 10.1016/j.epsr.2016.08.026.

[13] T. T. Nguyen and A. V. Truong, "Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm," Int. J. Elect. Power Energy Syst., vol. 68, pp. 233–242, Jun. 2015, doi: 10.1016/j.ijepes.2014.12.075.

[14] K. Mahmoud and M. Lehtonen, "Comprehensive analytical expressions for assessing and maximizing technical benefits of photovoltaics to distribution systems," IEEE Trans. Smart Grid, vol. 12, no. 6, pp. 4938–4949, Nov. 2021, doi: 10.1109/TSG.2021.3097508.

[15] K. Mahmoud and M. Lehtonen, "Simultaneous allocation of multitype distributed generations and capacitors using generic analytical expressions," IEEE Access, vol. 7, pp. 182701–182710, 2019, doi: 10.1109/ACCESS.2019.2960152.

[16] K. Mahmoud, N. Yorino, and A. Ahmed, "Optimal distributed generation allocation in distribution systems for loss minimization," IEEE Trans. Power Syst., vol. 31, no. 2, pp. 960–969, Mar. 2016,

[17] M. Shaheen, A. M. Elsayed, R. A. El-Sehiemy, and A. Y. Abdelaziz, "Equilibrium optimization algorithm for network reconfiguration and dis-

tributed generation allocation in power systems," Appl. Soft Comput., vol. 98, Jan. 2021, Art. no. 106867, doi: 10.1016/j.asoc.2020.106867.

[18] Onlam, D. Yodphet, R. Chatthaworn, C. Surawanitkun, A. Siritaratiwat, and P. Khunkitti, "Power loss minimization and voltage stability improvement in electrical distribution system via network reconfiguration and distributed generation placement using novel adaptive shuffled frogs leaping algorithm," Energies, vol. 12, no. 3, p. 553, Jan. 2019, doi: 10.3390/en12030553.

[19] V. V. V. S. N. Murty and A. Kumar, "Optimal DG integration and network reconfiguration in microgrid system with realistic time varying load model using hybrid optimisation," IET Smart Grid, vol. 2, no. 2, pp. 192–202, Jun. 2019, doi: 10.1049/iet-stg.2018.0146.

[20] H. B. Tolabi, M. H. Ali, S. B. M. Ayob, and M. Rizwan, "Novel hybrid fuzzy-bees algorithm for optimal feeder multi-objective reconfiguration by considering multiple-distributed generation," Energy, vol. 71, pp. 507–515, Jul. 2014, doi: 10.1016/j.energy.2014.04.099.

[21] K. Muthukumar and S. Jayalalitha, "Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks," Appl. Soft Comput., vol. 52, pp. 1262–1284, Mar. 2017, doi: 10.1016/j.asoc.2016.07.031.

[22] R. Syahputra, I. Robandi, and M. Ashari, "Reconfiguration of distribution network with DG using fuzzy multi-objective method," in Proc. Int. Conf. Innov. Manage. Technol. Res., May 2012, pp. 316–321, doi: 10.1109/ICIMTR.2012.6236410.

[23] R. Rajaram, K. S. Kumar, and N. Rajasekar, "Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with distributed generation (DG)," Energy Rep., vol. 1, pp. 116–122, Nov. 2015, doi: 10.1016/j.egyr.2015.03.002.

[24] Bayat, A. Bagheri, and R. Noroozian, "Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method," Int. J. Electr. Power Energy Syst., vol. 77, pp. 360–371, May 2016, doi: 10.1016/j.ijepes.2015.11.039.

[25] U. Raut and S. Mishra, "An improved sine–cosine algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems," Appl. Soft Comput., vol. 92, Jul. 2020, Art. no. 106293, doi: 10.1016/j.asoc.2020.106293.

[26] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation," IEEE Trans. Power Syst., vol. 28, no. 1, pp. 317–325, Feb. 2013, doi: 10.1109/TPWRS.2012.2197227.

[27] T. T. Nguyen, A. V. Truong, and T. A. Phung, "A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network," Int. J. Elect. Power Energy Syst., vol. 78, pp. 801–815, Jun. 2016, doi: 10.1016/j.ijepes.2015.12.030.

[28] M. Imran, M. Kowsalya, and D. P. Kothari, "A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks," Int. J. Elect. Power Energy Syst., vol. 63, pp. 461–472, Dec. 2014, doi: 10.1016/j.ijepes.2014.06.011.

[29] M. Esmaeili, M. Sedighizadeh, and M. Esmaili, "Multi-objective optimal reconfiguration and DG (distributed generation) power allocation in distribution networks using big bang-big crunch algorithm considering load uncertainty," Energy, vol. 103, pp. 86–99, May 2016, doi: 10.1016/j.energy.2016.02.152.

[30] Hamioud, A.; Sebaa, P.K. Genetic algorithms for the reconfiguration of electrical distribution networks. In Proceedings of the 2019 International Conference on Advanced Electrical Engineering (ICAEE), Algiers, Algeria, 19–21 November 2019; pp. 1–6.

[31] M. Sedighizadeh, M. Esmaili, and M. Esmaeili, "Application of the hybrid big bang-big crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems," Energy, vol. 76, pp. 920–930, Nov. 2014, doi: 10.1016/j.energy.2014.09.004.

[32] M. Abd El-Salam, E. Beshr, and M. Eteiba, "A new hybrid technique for minimizing power losses in a distribution system by optimal sizing and siting of distributed generators with network reconfiguration," Energies, vol. 11, no. 12, p. 3351, Nov. 2018, doi: 10.3390/en11123351.