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Optimal Placement Strategy of Distributed Generators based on Radial Basis Function Neural Network in Distribution Networks

Swati Gupta[a1], Akash Saxena[a2], Bhanu Pratap Soni[b]*

[1]M.Tech. Student, [2]Associate Professor

[a]Dept. of EE, Swami Keshvanand Institute of Technology, Jaipur, Rajasthan, INDIA

[b]Research Scholar, Dept. of EE, Malaviya National Institute of Technology, Jaipur, Rajasthan, INDIA-302017

Abstract

In order to minimize the power losses and improve the voltage profile of the distribution network, introduction of production decentralized, also called decentralized generators or distributed generators (DG), in distribution network plays an important role. The optimal placement and sizing of DG is necessary for profound DG potential. To solve this combinatorial problem, a radial basis function neural network based optimization technique is proposed in this paper. Training and Learning of the Neural Network (NN) has profuse importance while dealing with the real problems, however, the computation time associated with the progression put a question mark on the effectiveness of the approach. RBFNN with conventional learning algorithms does not achieve the desired speed and performance in the training process. To overcome this difficulty a heuristic technique Particle Swarm Optimization (PSO) is employed for efficient learning of the RBFNN. Network tested on IEEE-69bus system is used to evaluate the effectiveness of this method. The convergence of RBFNN-PSO is compared with Conventional RBFNN.

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Keywords: Distribution Networks;Distributed Generation (DG); Neural Networks; Particle Swarm Optimization (PSO); Radial Basis Function Neural Network (RBFNN)

* Corresponding author. Tel.: +91-978-290-7608.
E-mail address: er.bpsoni2011@gmail.com.

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1. Introduction

Distributed generation has been envisaged to play an escalating role in electrical power system in near future. The term distributed generation is used to refer small scale electricity generation. But till yet there is no consensus as to what exactly a small scale electricity generation is or how it can be defined. CIGRE defines distributed generation as the generation having a capacity of about 50 MW to 100 MW and placed at distribution side and that are neither centrally planned nor dispatched [1]. IEEE defines distributed generation as the generation of electricity by facilities that are smaller than the central generating system such they can be connected easily anywhere in the network.

The plenitude of the advantages of DG justifies the planning of electrical systems in the presence of DG. The benefits of DGs are site specific. DG devices can be cardinally placed in electrical power system for grid reinforcement, reducing power losses and on peak operating costs, improving voltage profiles and load factors, differing or eliminating for system upgrades and improving system integrity, reliability, and efficiency. Several approaches have been proposed for determining the optimal location of DG in open literatures. The major objective of DG placement technique is to minimize the power loss in the system. However the other objectives like improving the voltage profile, reliability, maximizing DG capacity, cost 1qazminimization etc. have also been considered in different studies.

It is very surprising to find all these approaches addressed with particular loading conditions, however in real time application these load levels are dynamic and it is probable that the approach presents erroneous results when subjected to a particular operating condition. Various approaches like Ant Colony Optimization, Evolutionary Algorithm (EA) and Particle Swarm Optimization (PSO) [2]-[5]. In [6], particle swarm optimization has been used for optimal placement of DG and the results are compared to the analytical approach. Further the approaches like Prime Dual Interior Point method [7], mixed integer nonlinear programming [8],[10], evolutionary programming (EP) technique [11], analytical approach [12]–[15], trade-off method [16], Hereford Ranch algorithm [17], linear programming technique [18], genetic algorithm(GA) technique [19], heuristic approaches [20], Classical Second Order method [21], Tabu Search approach [22], and Decision Theory approach have been employed to solve the DG placement problem in Distribution Networks.

This paper presents a Radial Basis Function Neural Network (RBFNN) based strategy to penetrate the effective locations and sizing of the DG in a Radial Distribution Network. To improve the computation speed and performance in the training process of RBFNN, Particle swarm optimization technique is employed. The proposed technique has been tested on 69 bus system. The results obtained from proposed technique is compared with results of conventional RBFNN and that of analytical approach.

2. Problem Formulation

Optimal DG allocation and sizing problem is formulated as a non-linear integer optimization with the objective of real power loss minimization of the system. The objective function for real power loss minimization may be given as follows

$$F_{Loss\min imization} = \min\left(P_{Loss}\right) = \sum_{k=1}^{N} I_k^2 R_k \tag{1}$$

Where

I_k is the feeder current loading.

R_k is the line resistance.

$F_{Loss\min imization}$ is the objective function for minimization of power losses.

P_{Loss} is the active power loss.

N is the total number lines in radial distribution system.

3. Computational Procedure

In this paper PSO serves two purposes at first PSO calculates the size and optimal location of DG and at second the tuning of RBFNN is carried out by the PSO. The brief description of PSO and RBFNN are given in following section.

3.1. Particle Swarm Optimization

The particle swarm optimization (PSO) technique is a population based optimization technique first proposed by Kennedy and Eberhart in 1995 inspired by social behaviour of bird flocking or fish schooling [6].PSO as an optimization tool provides a population based search procedure in which individuals called particles change their position (state) with time. In a PSO system particles fly around in a multidimensional search space. During its flight each particle adjusts its position according to its own experience (P_{best}) and according to its neighbour's experience (*gbest*), making use of the best position encountered by itself and its neighbors. This is expected to move the swarm toward the best solutions. Such methods are commonly known as heuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time etc.

3.2. Radial Basis Function Neural Network

The RBFNN is a feed forward neural network consisting of three layers namely, an input layer which feeds the values to each of the neurons in the hidden layer, a hidden function which consists of neurons with radial basis activation function and an output layer which contains neurons with linear activation function. The learning process for RBF neural networks is composed of initiating centers and widths for RBF units and computing weights for connectors of these units. Based on different applications of RBFNN, in the literature many learning strategies have been applied for changing the parameters of RBFNN during the training process. The conventional learning algorithm applied for real time application cannot satisfy the desired speed and performance in the training process. Hence, the optimum steepest descent learning algorithm is applied to improve the RBFNN training process with fewer epochs so as to make it faster and more accurate .A generic topology of RBFNN with k input and m hidden neurons is shown in Fig.1.

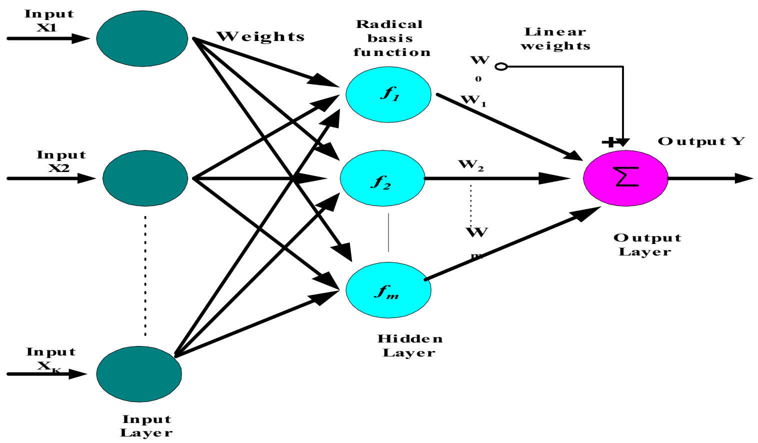

Fig. 1. A generic architecture of RBFNN

For the training of the RBFNN and considering a k dimensional input vector, X, the computed scalar values can be expressed as,

$$Y = f(X) = W_0 + \sum_{i=1}^{m} W_i \phi(D_i) \tag{2}$$

Where W_0 is the basis, W_i is the weight parameter, m is the number of neurons in the hidden layer and D_i is the RBF.

There are many basis functional choices possible for the RBF like spline, multi-quadratic, and Gaussian functions but the most widely used one is the Gaussian function. The Gaussian RBFNN is found not only suitable in generalizing a global mapping but also in refining local features without altering the already learned mapping.

In this study, the Gaussian function is used as the RBF and it is given by

$$\phi(D_i) = \exp\left(\frac{-D_i^2}{\sigma^2}\right) \tag{3}$$

Here σ is the radius of the cluster represented by the centre node (Spread) and usually called width, D_i is the distance between the input vector and X and all data centres.

The Euclidean norm is normally used to calculate the distance, D_i which is given by

$$D_i = \sqrt{\sum_{j=1}^{k} (X_j - f_{ij})^2} \tag{4}$$

Where f is the cluster center for any of the given neurons in the hidden layer.

In a RBNN, the estimated output vector, Y can be expressed as

$$Y = [y_i] = W\phi^T \tag{5}$$

Where $i = 1,2\ldots n$

Therefore the error vector, E and its respective sum squared error, J, which should be minimized through the learning process are defined as

$$E = Y_d - Y = Y_d - W\phi^T \tag{6}$$

$$J = \frac{1}{2} EE^T \tag{7}$$

It should be noted that in the conventional steepest descent algorithm, new weights are computed using the gradient of in the W as,

$$\left.\begin{aligned} OJ &= \frac{\partial J}{\partial W} \\ &= \frac{\partial\left(\left(\frac{1}{2}\right)EE^T\right)}{\partial W} \\ &= (Y_d - Y)\frac{\partial Y}{\partial W} \\ &= E\frac{\partial\left(W\phi^T\right)}{\partial W} \end{aligned}\right\} \tag{8}$$

$$\Delta W = OJ = E\phi \tag{9}$$

$$W_{new} = W_{old} + \lambda \Delta W \tag{10}$$

Where the coefficient λ is called learning rate which remains constant throughout the learning process.

Eq.(9) shows that the optimum direction of the delta weight vector in the sense of first order estimation, does not still specify the optimum length of J vector and the optimum learning rate(OLR).To achieve the OLR, the sum squared error of the new weights should be obtained using Eq. (5)-(10) as follows

$$\left.\begin{aligned} J(W)+\lambda\Delta W &= \frac{1}{2}\left(Y_d-(W+\lambda\Delta W)\phi^T\right)\left(Y_d-(W+\lambda\Delta W)\phi^T\right)^T \\ &= \frac{1}{2}\left(E-\lambda\Delta W\phi^T\right)\left(E-\lambda\Delta W\phi^T\right)^T \\ &= \frac{1}{2}EE^T-\lambda E\phi\Delta W^T+\frac{1}{2}\lambda^2\Delta W\phi^T\phi\Delta W^T \\ &= A+B\lambda+C\lambda^2 \end{aligned}\right\} \quad (11)$$

Where $A=\frac{1}{2}EE^T$, $B=-E\Phi\Delta W^T$ and $C=\frac{1}{2}\Delta W\phi^T\phi\Delta W^T$ are scaler constants. Thus, $J(W+\lambda\Delta W)$ is a quadratic function of λ with constant coefficients *A, B* and *C*. Therefore *J(λ)* defines a quadratic function of *Φ* with positive coefficients of the second order term. *J(λ)* can be minimized by taking its derivative as,

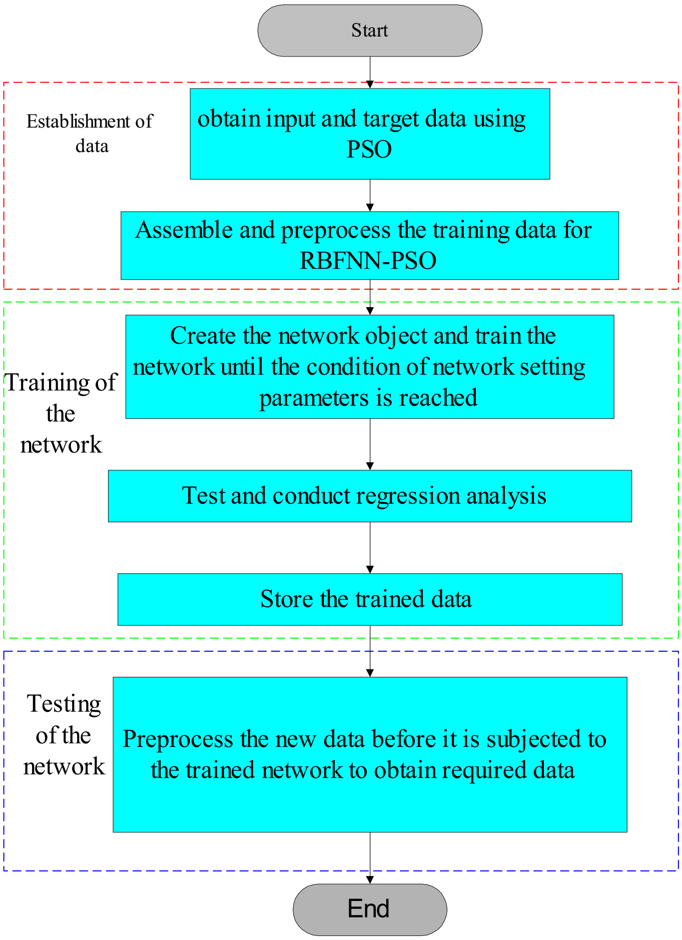

Fig.2. Implementation procedure for RBFNN-PSO

$$\frac{\partial J}{\partial \lambda} = \frac{\partial\left(A + B\lambda + C\lambda^2\right)}{\partial \lambda} = B + 2\lambda C = 0 \tag{12}$$

Hence

$$\lambda_{\min} = -\frac{B}{2C} = \frac{(E\Phi)}{\left(E\Phi\Phi^T\right)}\frac{(E\Phi)^T}{\left(E\Phi\Phi^T\right)^T} \tag{13}$$

This learning rate minimizes the J (λ), and so OLR can be expressed as,

$$\lambda_{opt} = \frac{(E\Phi)(E\Phi)^T}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \geq 0 \tag{14}$$

Using the above equation, the optimum delta weight vector can be determined as,
Hence,

$$\Delta W_{opt} = \lambda_{opt}\Delta W = \frac{(E\Phi)(E\Phi)^T E\Phi}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \tag{15}$$

For which the initial value for W is set with a random value.Fig.2 illustrates the flow chart for the implementation of proposed approach.

4. Numerical Results

In this paper PSO serves two purposes at first PSO calculates the size and optimal location of DG and at second the training of RBFNN is carried out by the PSO. The convergence characteristics of RBFNN (Conventional and PSO) are compared in fig. 5. Further Fig. 3 & 4 shows the value of losses and sizing of the DGs at each bus for a given operating condition, due to space limitations we are showing the results of Base case only. The proposed method is implemented using MATLAB 2013 and run on a Pentium IV CPU, 2.69 GHz, and 1.84 GB RAM computer [25].

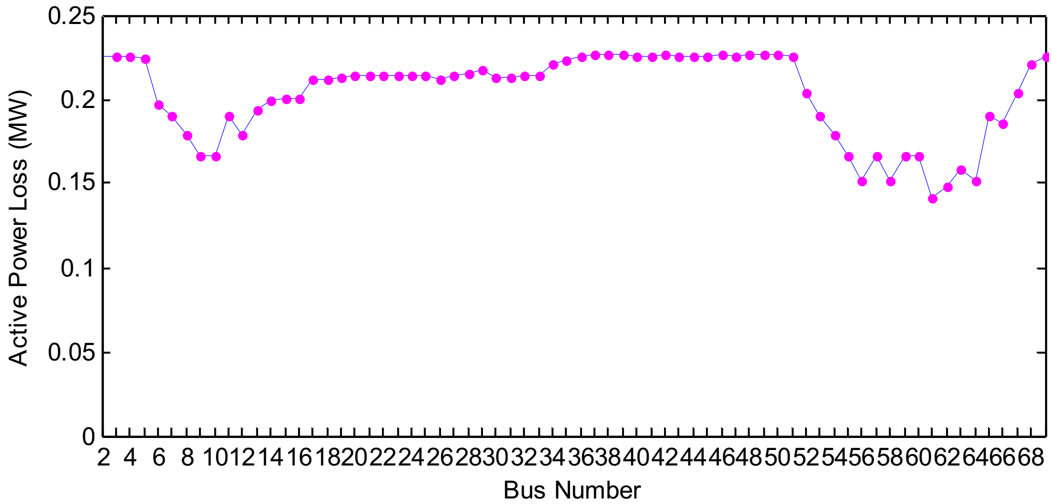

Fig.3. Active power loss at each bus of 69 bus system

For showing the effectiveness of proposed approach the DG size and locations are calculated by RBFNN and RBFNN-PSO, the results for the have been shown in the table I. RBFNN is trained through 110 datasets and target for the simulations are achieved through PSO algorithm. Out of these datasets 80 % are used for training and rest is used for testing purpose. A convergence characteristic is shown in fig.6 Mean Square Error (MSE) is decreased with RBFNN-PSO.

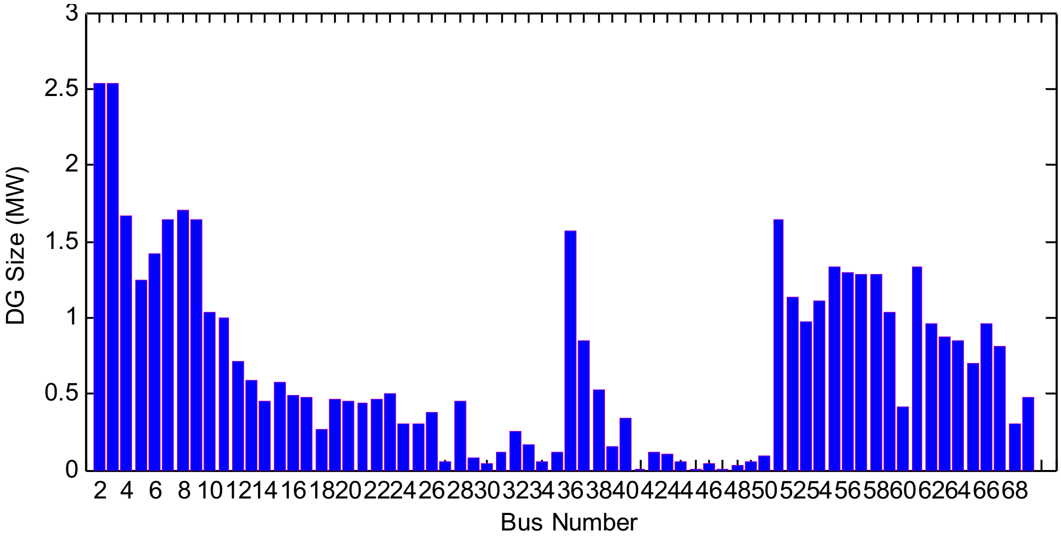

Fig.4. DG size at each bus of 69 bus system

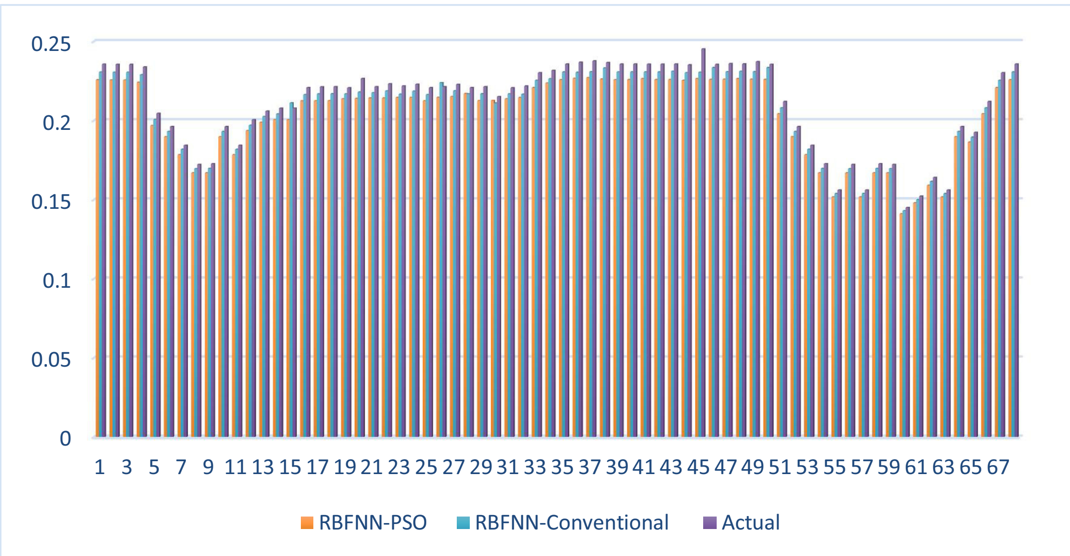

Fig.5. Active Power Loss at each bus of 69 bus system by all three methods

From fig.5 active power loss at each bus can be calculated by all three methods, however the RBFNN- PSO outperformed over the conventional methods and MSE obtained from the RBFNN PSO is achieved the error margin 1e-6, critical bus identification is done on the basis of amount of the loss reduced by placing the appropriate size DG.

Following are the critical observations on the simulations:

- RBFNN-PSO outperformed and achieved less MSE in a reduced time, this fact is exhibited by the convergence characteristics of both methods in Fig.6.
- Normally in power system operating conditions vary in wide range, in previous approaches [15]-[22] the system is subjected to particular operating conditions. DG allocation is a part of planning of the power system, where the system condition are dynamic so it is quite meaningful to perform this analysis with neural networks.

Table 1. Critical Bus locations and optimal DG size

RBFNN-PSO	RBFNN	Actual	Bus No.
2.5337292	2.4927129	2.4516473	2
2.5344705	2.4929842	2.4515396	3
1.6714367	1.6427309	1.6131483	4
1.4180723	1.4000366	1.3784233	6
1.6421545	1.6172986	1.594674	7
1.707318	1.6826096	1.6579573	8
1.6453316	1.6216765	1.5961642	9
1.5639923	1.5396982	1.5176606	36
1.6484458	1.625542	1.6025577	51
1.3374691	1.3187972	1.2992333	55
1.293703	1.2746734	1.2562987	56
1.2853037	1.2659396	1.2469236	57
1.283714	1.2578746	1.2456045	58
1.3365891	1.3161462	1.295288	61

- Table 1 shows the critical buses and optimal size of DGs. The power losses reduced due to the DG placement shown in Fig.5. In planning of the power system, this analysis shows an insight to locate the effective place in a complex distribution network for minimizing the power loss.

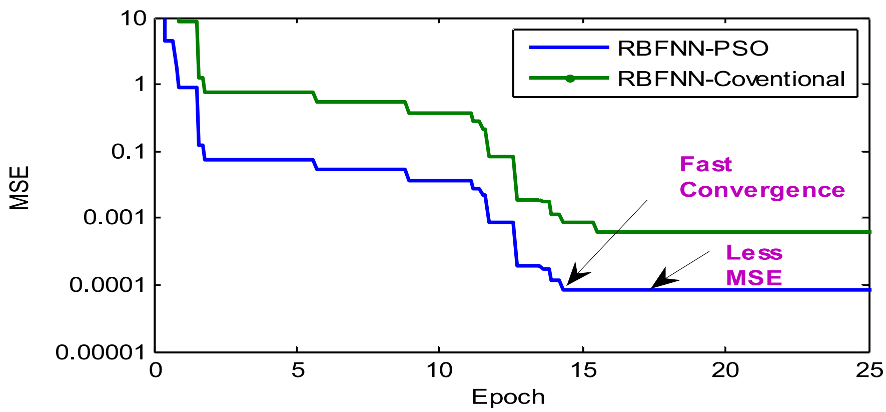

Fig. 6. Comparison of Convergence characteristics of RBFNN-PSO and BRFNN

5. Conclusion

This paper proposes a RBFNN based approach to penetrate the DG at effective locations of in IEEE-69 bus distribution system. DG placement is carried out on each bus using PSO, which is taken as the target for the neural network than training of RBFNN is improved by PSO and The comparison of the same is carried out with conventional Training pattern,. It is observed that RBFNN- PSO not only achieve the required target but also achieve it in the less time.

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