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Saifee Kanjetawala

saifee.kanjeta@gmail.com

Krishna School of Emerging Technology and Applied Resaerch https://orcid.org/0000-0002-4394-6205

SAMIR PATEL

Krishna School of Emerging Technology and Applied Resaerch

DATTESH JOSHI

Krishna School of Diploma Studies

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1. Saifee Kanjetawala
PhD Scholar
Electrical Engineering Department
Krishna School of Emerging Technology and Applied Research (KSET), KPGU, Vadodara
saifee.kanjeta@gmail.com

2. Dr. Samir Patel
Associate Professor
Electrical engineering department
Krishna School of Emerging Technology and Applied Research (KSET), KPGU, Vadodara
samirpatel.ee@gmail.com

3. Dr. Samir Patel
Associate Professor
Electrical engineering department
Krishna School of Diploma Studies (KSDS), KPGU, Vadodara
datteshjoshi.ee@gmail.com

Abstract- Distributed Generation (DG) is expected to assume an increasingly significant role in the electrical power system soon. Nonetheless, the advantages of DGs cannot be realized if they are not strategically located. The use of DG units enhances the efficiency of the distribution system. The use of distributed generation (DG) is associated with minimizing losses and improving voltage levels in distribution feeders. This document introduces a strategy utilizing a Radial Basis Function Neural Network (RBFNN) to identify the optimal locations and sizes of Distributed Generators (DG) in a Radial Distribution Network. The training and learning of the Neural Network (NN) hold significant importance when addressing real-world issues; however, the time required for computation raises concerns about the approach's effectiveness. RBFNN utilizing traditional learning algorithms fails to attain the expected speed and efficiency during training. A heuristic approach, Particle Swarm Optimization (PSO), is used to efficiently train the RBFNN and address this challenge. The convergence of RBFNN-PSO is contrasted with traditional RBFNN. The effectiveness of the suggested method is evaluated on the conventional IEEE-33 bus system.

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

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1. INTRODUCTION

In recent years, the modern power system has emerged as a complex network consisting of different electrical drives, loads and moreover the integration of multiple utility devices in both transmission side and generation side. Escalating population and competitive business environment makes the operating conditions stressed. In early years less emphasis was given to improve the efficiency of a distribution networks as the stability and reliability issues were dominant. Recently DGs have attracted a serious attention of electrical market due to their potential use in some issues like voltage deregulation in power system, increasing power consumption and shortage of transmission capacities. But the benefits of the distributed generator are site specific. Hence optimization and sizing of DG is necessary for maximizing the DG potential benefits.

DGs are referred as embedded generations, CIGRE define the DGs as the power plants having maximum capacity of 100 MW. These DGs are connected in the distribution networks and these connections are neither centrally planned nor dispatched [1]. Classification of DGs is done on the basis of the power injections.

Type I: DG capable of injecting real power only, like photovoltaic, fuel cells etc.

Type II: DG capable of injecting reactive power only to improve the voltage profile fall in type-II DG, e.g. kvar compensator, synchronous compensator, capacitors etc.

Type III: DG capable of injecting both real and reactive power, e.g. synchronous machines.

Type IV: DG capable of injecting real but consuming reactive power, e.g. induction generators used in the wind farms.

In past various approaches have been applied to penetrate the DG location and sizing in distribution network. These approaches place DG in the system with the aim of minimizing the power losses. Surprisingly all these approaches are addressed with particular loading conditions, however in real time application these load levels are dynamic and may be the approach gives 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[4] a new improved harmony search algorithm to address the placement of DGs in distribution networks. The results are compared with Non dominated Sorting Genetic Algorithm (NSGA) and Particle Swarm Optimization (PSO) .In [7] placement of renewable sources namely wind and solar was done with the help of evolutionary programming. Authors reported two operation strategies, namely "turning off wind turbine generator" and "clipping wind turbine generator output". These strategies were adopted to restrict the wind power dispatch to a specified fraction of system load for system stability consideration. Further the approaches like Prime Dual Interior Point method [8], mixed integer nonlinear programming [9],[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 [23] have been employed to solve the Dg placement problem in Distribution Networks.

2. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a stochastic population based evolutionary algorithm for problem solving. Particle swarm optimization is a stochastic, population-based evolutionary computer algorithm for problem solving. It is a kind of swarm intelligence that is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. The particle swarm optimization algorithm was first described in 1995 by JAMES KENNEDY and RUSSELL C.EBERHART [24]. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience (This value is called Pbest), and according to the experience of a neighboring particle (This value is called Gbest), makes use of the best position encountered by itself and its neighbor **fig.1**.

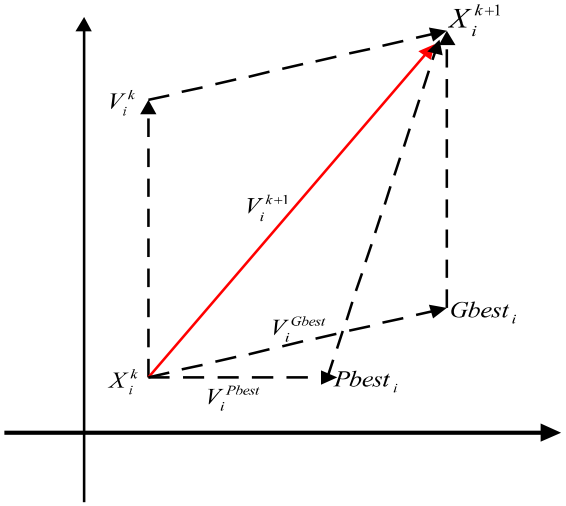


Fig.1 : Basic concept of PSO

Where

V_i^k is current velocity of particle *i* at iteration *k.*

V_i^{k+1} is modified velocity of particle *i.*

X_i^k is current position of particle *i* at iteration *k* .

X_i^{k+1} is modified position of particle i.

V_i^{Pbest} is velocity based on $Pbest$.

V_i^{Gbest} is velocity based on $Gbest$.

This modification can be represented by concept of velocity. Velocity of each agent can be modified by following equation:

$$V_i^{k+1} = wV_i^k + c_i\, rand_1 * (pbest_i - X_i^k) + c_i\, rand_2 * (gbest_i - X_i^k)$$

Using above equation, a certain velocity, which gradually gets close to $pbest$ and $gbest$ can be calculated. The current position (searching point in the solution space) can be modified by following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1}$$

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. 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.2.

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

$$Y = f(X) = W_0 + \sum_{i=1}^{m} W_i \Phi(D_i) \qquad (1)$$

Where W_0 is the bais, $W_i$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

$$\phi(D_i) = \exp\left|\frac{D_i^2}{\sigma^2}\right| \qquad (2)$$

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

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

$$D_i = \sqrt{\sum_{j=1}^{k}(X_j - f_{ji})^2} \qquad (3)$$

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

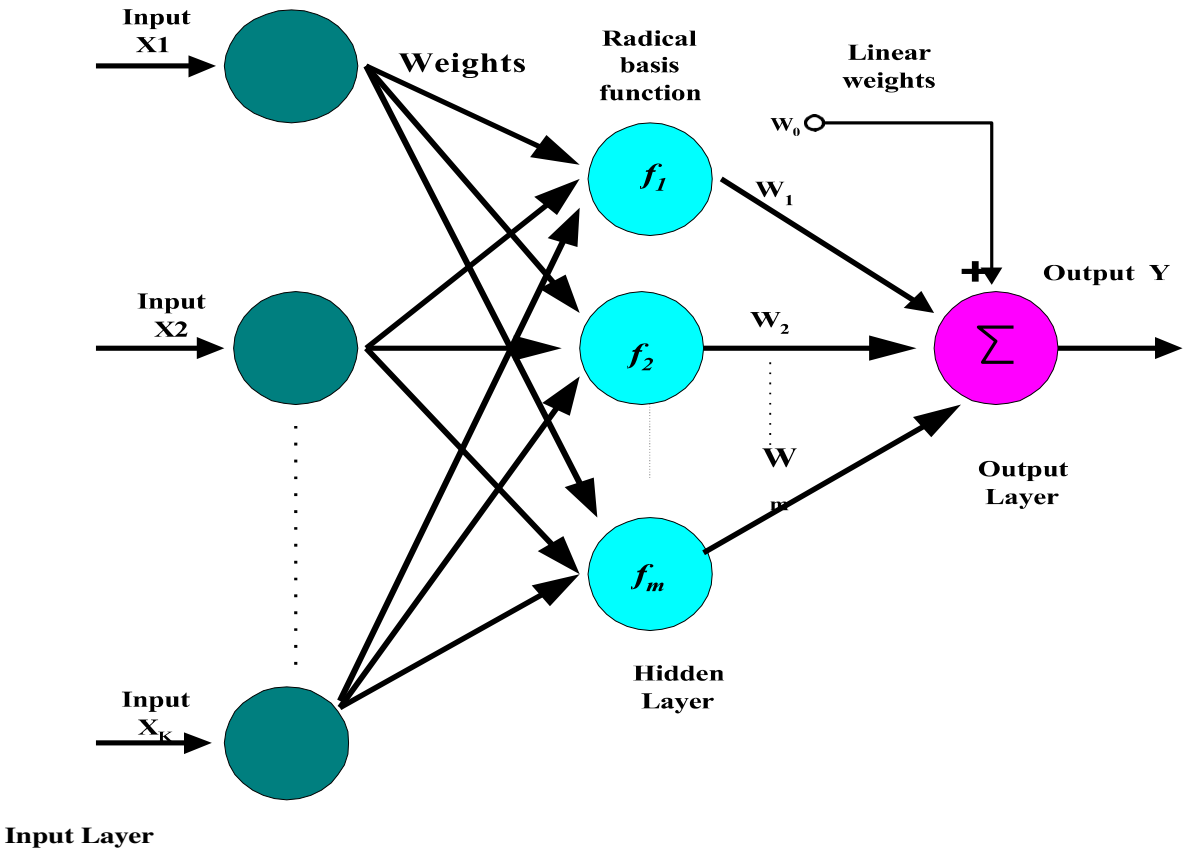


Fig. 2 : A Generic architecture of RBFNN

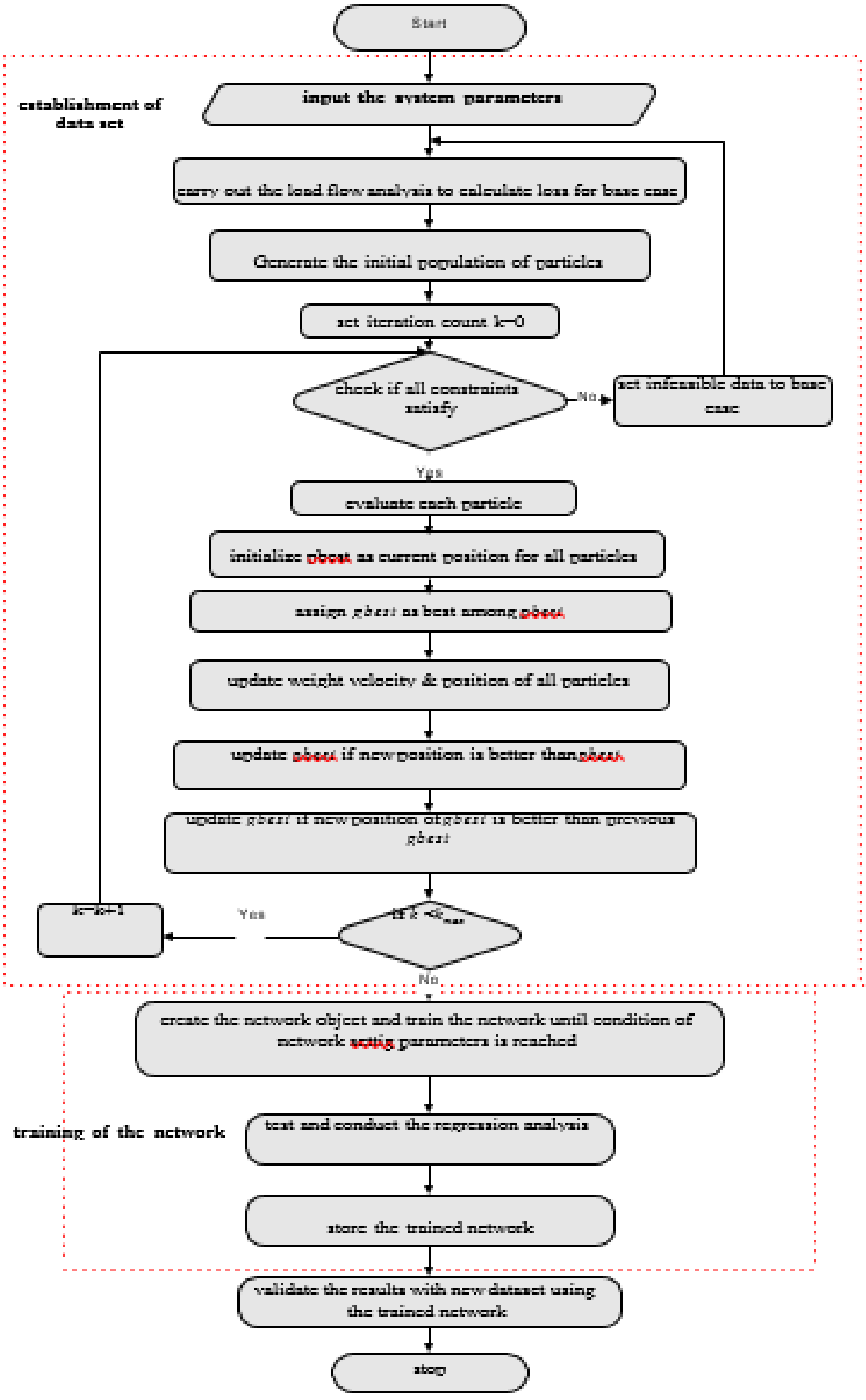


Fig.3. *: Flowchart for the proposed methodology*

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

$$Y = [\, y \,] = W\phi^{T} \tag{4}$$

$$i = 1,2 \ldots n$$

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

$$E = Y_d - Y = Y_d - W\phi^{T} \tag{5}$$

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

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

$$OJ = \frac{\partial J}{\partial W} = \frac{\partial\left(\left(1/2\right)EE^{T}\right)}{\partial W} = \left(Y_d - Y\right)\frac{\partial Y}{\partial W} = E\frac{\partial\left(W\phi^{T}\right)}{\partial W} = -E\Phi \tag{6}$$

$$\Delta W = OJ = E\Phi \tag{7}$$

$$W_{new} = W_{old} + \lambda\Delta W \tag{8}$$

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

Eq.(7)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 Eqs(4)-(8)as follows:

$$J(W) + \lambda\Delta W = \frac{1}{2}\left(Y_d - \left(W + \lambda\Delta W\right)\Phi^{T}\right)\left(Y_d - \left(W + \lambda\Delta W\right)\Phi^{T}\right)^{T}$$

$$= \frac{1}{2}\left(E - \lambda\Delta W\Phi^{T}\right)\left(E - \lambda\Delta W\Phi^{T}\right)^{T}$$

$$= \frac{1}{2} EE^{T}$$

$$- \lambda E\Phi\Delta W^T + \frac{1}{2}\lambda^2 \Delta W \Phi^T \Phi\Delta W^T - \frac{1}{2}$$

$$= A + B\lambda + C\lambda^2 \quad (9)$$

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,

$$\frac{\partial J}{\partial \lambda} = \frac{\partial\left(A + B\lambda + C\lambda^2\right)}{\partial \lambda} = B + 2\lambda C = 0 \qquad (10)$$

Hence,

$$\frac{B}{\lambda_{\min}} = -\frac{\left(E\Phi\right)}{2C} = \frac{\left(E\Phi\right)^T}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \qquad (11)$$

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

$$\lambda_{opt} = \frac{\left(E\Phi\right)\left(E\Phi\right)^T}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \geq 0 \qquad (12)$$

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

$$\Delta W_{opt} = \lambda_{opt}\,\Delta W = \frac{\left(E\Phi\right)\left(E\Phi\right)^T E\Phi}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \qquad (13)$$

Hence,

$$\Delta W_{opt} = \lambda_{opt}\,\Delta W = \frac{\left(E\Phi\right)\left(E\Phi\right)^T E\Phi}{\left(E\Phi\Phi^T\right)\left(E\Phi\Phi^T\right)^T} \qquad (14)$$

For which the initial value for W is set with a random value.

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. 6. Further Fig. 4 & 5 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 [26].

For showing the effectiveness of proposed approach the DG size and locations are calculated by RBFNN and RBFNN-PSO, the results for the same under four operating conditions has 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.

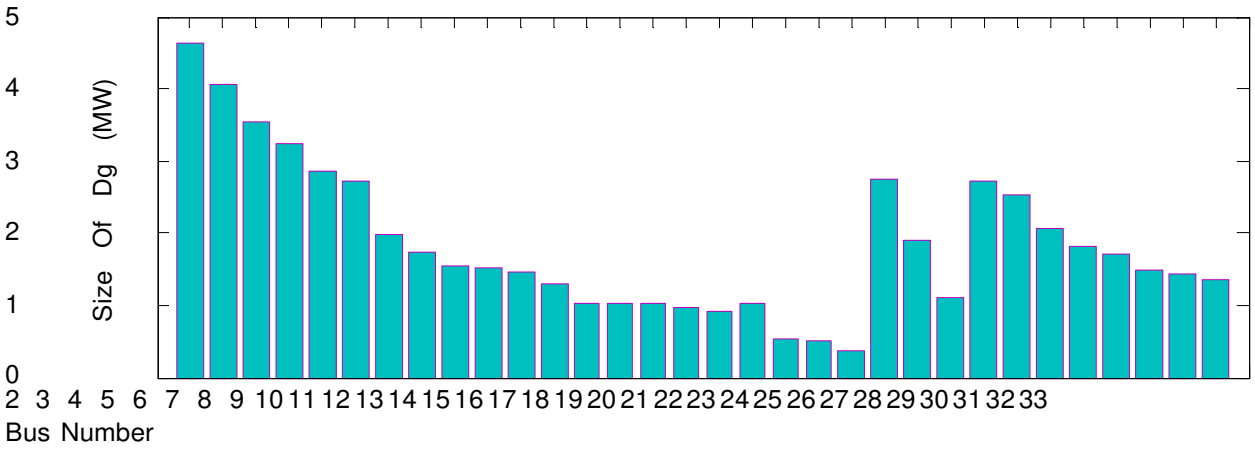


Fig.4: Size of DG at each bus of 33 bus system for base case

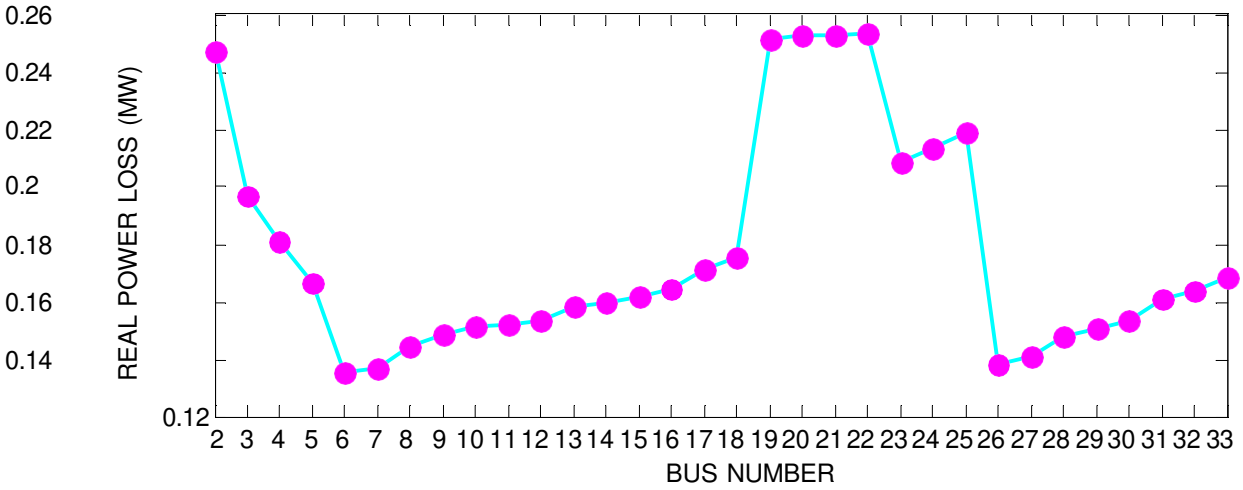


Fig.5: Active power loss at each bus of 33 bus system for base case

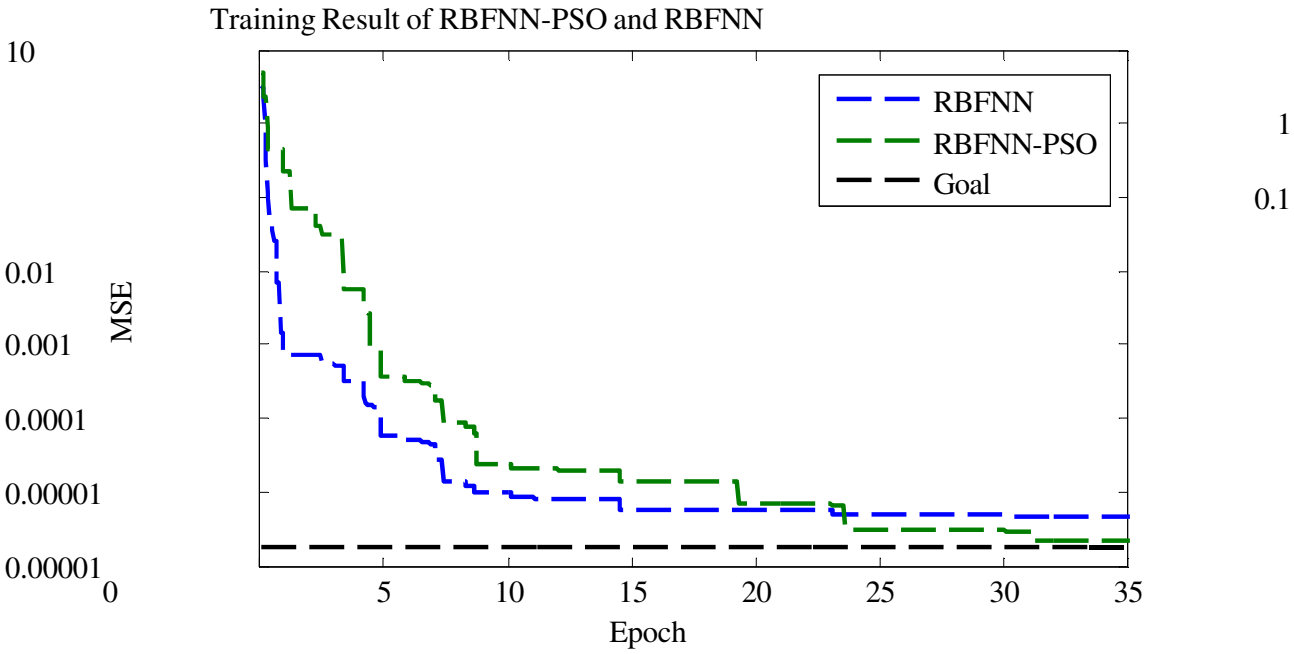


Fig.6: Comparison of Convergence between two methods

Table: I Calculation of DG sizing and Power loss

Conventional RBFNN			PSO-RBFNN		Actual	
Bus no	size	loss	size	loss	size	Loss
2	4.17861	0.203243	4.09476	0.19577	4.193082	0.205534
3	3.76876	0.178767	3.678971	0.15676	3.688829	0.164051
4	3.23452	0.176121	3.209813	0.14238	3.213348	0.151148
5	2.84672	0.130789	2.7486	0.136521	2.940986	0.138808
6	2.57861	0.109327	2.53812	0.108994	2.618548	0.113442
7	2.462574	0.109844	2.45743	0.109665	2.482574	0.114444
8	1.793295	0.119252	1.80787	0.118725	1.810295	0.120725
9	1.569087	0.119487	1.55998	0.119847	1.580588	0.124069
10	1.448975	0.119457	1.40489	0.109637	1.414734	0.126453
11	1.365416	0.119436	1.34767	0.119730	1.388376	0.126934
12	1.35967	0.119805	1.34008	0.118572	1.340396	0.128015
13	1.00942	0.127591	1.00901	0.127592	1.009708	0.131759
14	1.02687	0.128722	1.026019	0.128242	1.027199	0.132426
15	1.009135	0.13275	1.009594	0.134644	1.013569	0.134679
16	0.943602	0.136542	0.937872	0.129898	0.973602	0.13796
17	0.864398	0.139281	0.84371	0.13912	0.877957	0.143721
18	0.829365	0.143940	0.81787	0.13939	0.831601	0.146943
19	1.0156425	0.209945	1.014676	0.209425	1.016266	0.210014
20	0.477945	0.209191	0.465379	0.210387	0.485379	0.211395
21	0.404389	0.209572	0.402769	0.2090115	0.403369	0.211508
22	0.337812	0.2107875	0.326521	0.2109612	0.343381	0.211845
23	2.423789	0.169360	2.490954	0.1693577	2.501834	0.173602
24	1.721787	0.176505	1.7281321	0.1717705	1.732086	0.177705
25	1.078786	0.181217	1.077711	0.1791322	1.07996	0.182927
26	2.456676	0.114914	2.461321	0.114910	2.477206	0.1154
27	2.278908	0.116591	2.276812	0.1152617	2.309008	0.117869
28	1.865451	0.12187	1.850091	0.1201211	1.875148	0.123658
29	1.645429	0.1243427	1.6312421	0.1232321	1.66622	0.125988
30	1.545421	0.1265445	1.5312176	0.125411	1.559048	0.127926
31	1.345132	0.1329987	1.32121	0.1321132	1.36753	0.134132
32	1.310998	0.1357551	1.310787	0.1343236	1.311423	0.136555
33	1.039898	0.140121	1.038788	0.140031	1.040618	0.140064

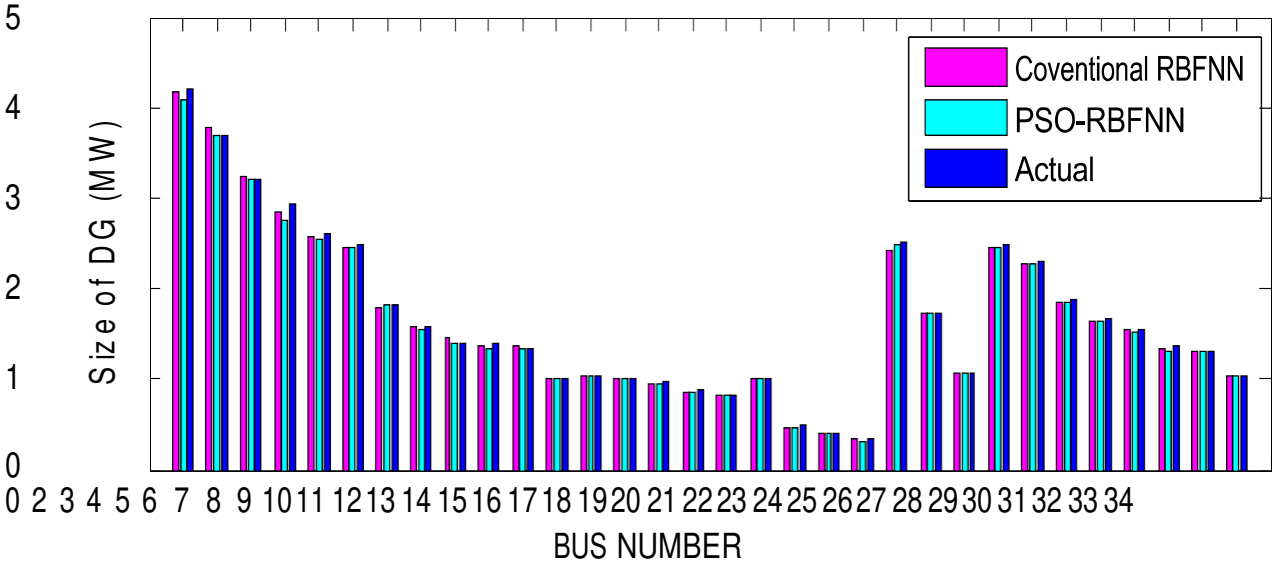


Fig.7: Comparative analysis of dg size at each bus with different algorithms

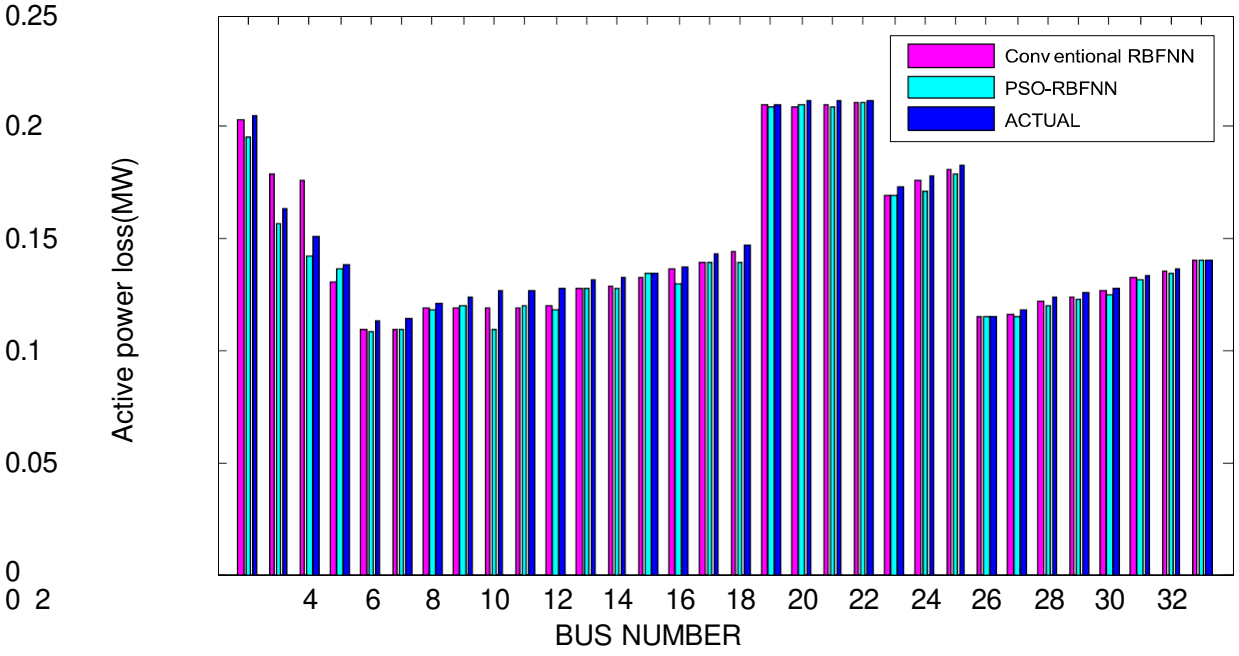


Fig.8: Comparative analysis of losses at each bus with different approaches

Fig.7 and 8 shows the comparative analysis of losses and DG size is calculated with RBFNN and RBFNN-PSO it is observed that the values obtained from RBFNN-PSO is much less than the RBFNN conventional and it is more close with the actual values.

5. Conclusion

The integration of distributed generation in the distribution network is a traditional issue in this intricate and practical power system. This article suggests an innovative method utilizing RBFNN. The IEEE-33 bus test system for the Distribution Network is selected to demonstrate the suggested method. The convergence features illustrating the effectiveness of booth techniques are presented, and it is noted that MSE is reached by RBFNN-PSO. Improved convergence and summarized findings.

Indicates that outcomes from RBFNN-PSO reached 10e-5 MSE. The suggested method achieves successful placements of DGs

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References

1. CIGRE, “Impact of increasing contribution of dispersed generation on the power system”, *Working Group37.23.* 1999.
2. Falaghi, H.; Haghifam, M.; Singh, C., "Ant Colony Optimization-Based Method for Placement of Sectionalizing Switches in Distribution Networks Using a Fuzzy Multiobjective Approach," *Power Delivery, IEEE Transactions on*, vol.24, no.1, pp.268,276, Jan. 2009.
3. El-Zonkoly, A.M., "Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation," *Generation, Transmission & Distribution, IET* , vol.5, no.7, pp.760,771, July 2011.
4. Nekooei, K.; Farsangi, M.M.; Nezamabadi-pour, H.; Lee, K.Y., "An Improved Multi-Objective Harmony Search for Optimal Placement of DGs in Distribution Systems," *Smart Grid, IEEE Transactions on*, vol.4, no.1, pp.557, 567, March 2013.
5. Chandrasekhar Yammani, Sydulu Maheswarapu, Sailajakumari Matam, “Multiobjective Optimization for Optimal Placement and Size of DG using Shuffled Frog Leaping Algorithm”, Energy Procedia, vol. 14, pp.990-995, 2012.
6. Satish Kansal, Vishal Kumar, Barjeev Tyagi, Optimal placement of different type of DG sources in distribution networks, International Journal of Electrical Power & Energy Systems, vol.53, pp 752-760, December 2013
7. Khatod, D.K.; Pant, V.; Sharma, J., "Evolutionary programming based optimal placement of renewable distributed generators," *Power Systems, IEEE Transactions on* , vol.28, no.2, pp.683,695, May 2013.
8. T.Q. D. Khoa, P. T. T.Binh, and H. B. Tran, “Optimizing location and sizing of distributed generation in distribution systems,” in *Proc. 2006 IEEE PES Power Syst. Conf. Expo.*, pp. 725–732.
9. Y. M. Atwa and E. F. El-Saadany, “Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems,” *IET Renew. Power Gen.*, vol. 5, pp. 79–88, Jan. 2011.
10. Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy,“Optimal renewable resources mix for distribution system energy loss minimization,” *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 360–370,Feb. 2010.
11. T. K. A. Rahman, S. R. A. Rahim, and I. Musirin, “Optimal allocation and sizing of embedded generators,” in *Proc. 2004 National Power and Energy Conf.*, pp. 288–294.
12. C. Wang and M. H. Nehrir, “Analytical approaches for optimal placement of distributed generation sources in power systems,” *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2068–2076, Nov. 2004.
13. T. Gozel andM. H. Hocaoglu, “An analyticalmethod for the sizing and siting of distributed generators in radial systems,” *Elect. Power Syst. Res.*, vol. 79, pp. 912– 918, Jun. 2009.
14. D. Q. Hung and N. Mithulananthan, “Multiple distributed generator placement in primary distribution networks for loss reduction,” *IEEE Trans. Ind. Electron.*, to be published.

15. G. Carpinelli, G. Celli, S. Mocci, F. Pilo, and A. Russo, "Optimisation of embedded generation sizing and siting by using a double trade-offmethod," *Proc. Inst. Elect. Eng. Gen., Transm., Distrib.*, vol. 152, pp.503–513, Jul. 2005.
16. L. F. Ochoa and G. P. Harrison, "Minimizing energy losses: Optimal accommodation and smart operation of renewable distributed generation,"*IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 198–205, Feb. 2011.
17. J. O. Kim, S. W. Nam, S. K. Park, and C. Singh, "Dispersed generation planning using improved Hereford ranch algorithm," *Elect. Power Syst. Res.*, vol. 47, pp. 47–55, Oct.1998.
18. A. Keane and M. O'Malley, "Optimal allocation of embedded generation on distribution networks," *IEEE Trans. Power Syst.*, vol. 20, no.3, pp. 1640–1646, Aug. 2005
19. G. Celli, E. Ghiani, S. Mocci, and F. Pilo, "A multiobjective evolutionary algorithm for the sizing and siting of distributed generation,"*IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 750–757, May 2005.
20. W. El-Khattam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama,"Optimal investment planning for distributed generation in a competitive electricity market," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1674–1684, Aug. 2004.
21. N. S. Rau and Y.-H. Wan, "Optimum location of resources in distributed planning," *IEEE Trans. Power Syst.*, vol. 9, no. 4, pp.2014–2020, Nov. 1994.
22. K. Nara, Y. Hayashi, K. Ikeda, and T. Ashizawa, "Application of Tabu search to optimal placement of distributed generators," in *Proc. 2001 IEEE PES Winter Meeting*, vol. 2, pp. 918–923
23. G. Celli and F. Pilo, "MV network planning under uncertainties on distributed generation penetration," in *Proc. 2001 IEEE PES Summer Meeting*, vol. 1, pp. 485–490.
24. S. H. Karaki, R. B. Chedid, and R. Ramadan, "Probabilistic performance assessment of autonomous solar-wind energy conversion systems," *IEEE Trans. Energy Convers.*, vol. 14, no. 3, pp. 766–772, Sep. 1999.
25. Kennedy, J. and Eberhart, R. C. Particle swarm optimization. Proc. IEEE int'l conf. on neural networks Vol. IV, pp. 1942-1948. IEEE service center, Piscataway, NJ, 1995.
26. MATLAB, Available: http://www.mathworks.com.

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Authors' Contributions:

First Author's Name: **Saifee Kanjetawala**

1) Idea & Conceptualization
2) Research & Investigation
3) Data Curation
4) Analysis
5) Funding Acquisition
6) Methodology
7) Project Administration
8) Software and Simulation
9) Verification
10) Original Draft Preparation
11) Revise & Editing

Second Author's Name: **Samir Patel**

1) Supervision
2) Verification

Third Author's Name: **Dattesh Joshi**

1) Supervision
2) Verification