Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 2434 – 2443

doi:10.3906/elk-1602-197

A novel generation and capacitor integration technique for today's distribution systems

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Received: 15.02.2016 • **Accepted/Published Online:** 20.09.2016 • **Final Version:** 29.05.2017

Abstract: In this paper, the problem of optimally placing shunt capacitors and generators in radial distribution systems is handled and a new calculation technique based on wavelet neural network (WNN), which is computationally effective compared to well-known techniques, is proposed. The objectives for the proposed method are simply selected as the minimum cost of peak power and losses and maximum voltage stability. The suggested optimization technique is tested on various IEEE radial buses and then compared to the well-known methods in the literature, i.e. golden section search, grid search, and Acharya's heuristic method. The proposed and conventional methods are applied to well-known IEEE buses to see the performances of the suggested technique. The results demonstrate that WNN provides an efficient solution to the placement of both shunt capacitors and distributed generators for power distribution systems.

Key words: Capacitor planning, optimization, renewable generation, smart grid, wavelet neural network

1. Introduction

Among energy sources, electrical energy is inevitable and should be supplied to the end-users while taking into account power quality issues. Today's energy companies should make additional efforts to meet the required demand for energy, resulting in an increase in power generation (distributed generations), as well as the use of energy with the highest efficiency.

The main way to increase the efficiency of energy use is to minimize losses. Furthermore, high power quality is expected in electrical distribution systems. The most effective way to improve the power quality in electrical networks requires minimizing the losses and increasing voltage stability. This is simply achieved by compensating reactive power. Optimal placement of shunt capacitors and distributed generations stand out to achieve them effectively [1–3].

If reactive power is not properly compensated, power losses occur and nodal voltage stability decreases. In this case, the efficient use of electrical power is not mentioned. This is also true if the capacitors are installed in a wrong node (bus). Therefore, optimal placing of shunt capacitors is of great importance [4,5].

In recent years, the electric power distribution network has started to include distributed generating sources (DGs) with different characteristics. DGs mostly consist of renewable sources within the range of 10 kW–10 MW and are designed to work either parallel to a grid or alone. The optimal placement of DGs has positive impacts on a power grid, such as minimizing losses and harmonics, and increasing the voltage and frequency stability, and power quality indices in a way similar to capacitor placing. It is for the reasons summarized above that the efficient use and placing of DGs in power distribution systems is so important [6,7].

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When the concept of DG is mentioned, generation technology usually comes to mind. In fact, it primarily deals with the concept of planning and operation in terms of electric distribution systems. While the load flow is from the generated site to the end-user in a traditional power network, when DGs are used it causes problems due to two-way load flow. To avoid these problems, a DG should be installed on a suitable bus. This helps to reduce problems such as voltage swell and flicker, resulting in a better voltage and frequency profile with minimum loss over the network [8,9].

Consequently, the optimal placement of both shunt capacitors and DGs has caught the attention of many scholars. To overcome this obstacle, different techniques and computational methods for optimal location/installation have been proposed in recent years [10].

There are mainly three optimization techniques used: conventional, artificial intelligence, and hybrid techniques. The 2/3 rule [11], analytical techniques [12,13], power flow methods [14], and nonlinear programming methods [15,16] are the major methods currently used in distribution systems. Evolutionary algorithms [17], simulated annealing [18], differential evolution [19,20], particle swarm [21,22], fuzzy systems [23], ant colony [24], cuckoo search [25], imperialist competition [26,27], tabu search [28], artificial bee colony [29], and firefly [30] are the major methods currently used in distribution systems.

This paper presents a different and simple capacitor/DG localization and integration technique based on a wavelet neural network (WNN). Wavelet functions are selected using the criteria of minimum description length while the decomposition levels are selected using minimum description length Shannon's entropy method, which provides less computational burden compared to classical usage of wavelet methods. The major IEEE bus examples, such as 12 bus and 33 bus, with their DG options are used to test the traditional and WNN approaches. The efficiencies of all algorithms are then compared with each other [31].

2. Formulation of the objective functions

Optimal placing problems for shunt capacitors and DGs can be overcome to include nonlinear objective functions such as minimizing power losses, decreasing installation costs, and enhancing voltage profile and overall system stability. These objective functions are taken into account for well-known radial distribution systems under analysis [32]. Mathematical representation of the selected objective functions is described in Eq. (1).

$$Min(pl + k_1 vq + k_2 vs + k_3 lb) \tag{1}$$

In Eq. (1), *pl*, *vq*, *vs*, and *lb* are the objective functions with the penalty coefficients k_1, k_2, and k_3. The coefficients k_1, k_2, and k_3 are chosen as penalty and their values can simply be defined according to the importance degree of selected objective functions.

2.1. Power losses (pl)

The prevention of active power losses can be maintained by adding capacitors and DGs where appropriate in the power distribution grid. The result will yield a reduction in active power losses and improve the efficiency.

Eq. (2) gives the calculation of active power losses.

$$pl = \sum_{i=2}^{nb_{tot}} (P_{bi} - P_{cbi} - V_{mi} V_{ni} Y_{ni} \cos\{\delta_{mi} - \delta_{ni} + \theta_{ni}\}), \tag{2}$$

where nb_{tot} is the total number of buses, P_{bi} is the active power output at bus n_i, P_{cbi} is the active power demand at n_i bus, V_{mi} is the voltage bus of m_i, V_{ni} is the voltage at n_i bus, Y_{ni} is the admittance matrix between n_i and m_i buses, δ_{mi} is the phase angle of voltage bus at bus m_i, δ_{ni} is the voltage phase angle at bus n_i, and θ_{ni} is the phase angle.

2.2. Maximizing voltage quality (vq)

Maximizing voltage quality as an objective function is given in Eq. (3).

$$vq = \sum_{ni=1}^{nb_{tot}} (V_{ni} - V_{rated})^2, \tag{3}$$

where V_{rated} is the rated voltage in pu.

2.3. Voltage stability (vs)

A simple distribution part of the power grid is shown in Figure 1. The optimal placement problem of capacitors and DGs is solved, increasing the voltage stability of the distribution busses (sending or receiving as in Figure 1). The main calculation employs load flow studies for this purpose [33].

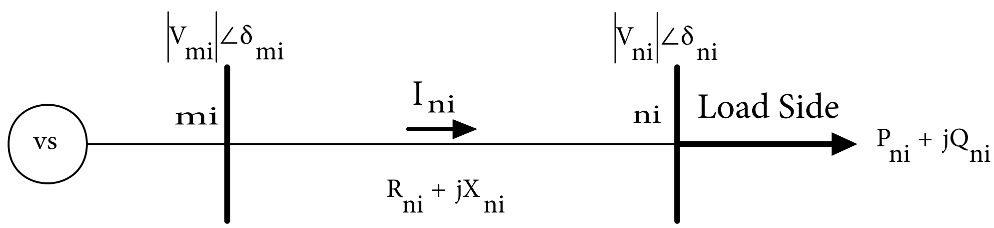

Figure 1. A simple two-end radial distribution network.

In Figure 1, m side represents the sending bus, while n side represents the receiving bus. The load is connected to n bus that requires voltage stability in terms of power quality concept. This index can be defined as in Eq. (4).

$$vs = |V_{mi}|^4 - 4\left[P_{ni}(n_i)R_{ni} + Q_{ni}(n_i)X_{ni}\right]|V_{mi}|^2 - 4\left[P_{ni}(n_i)R_{ni} + Q_{ni}(n_i)X_{ni}\right]^2 \tag{4}$$

The vs can also be modified as in Eq. (5).

$$vs_{\bmod ified} = \tfrac{1}{vs(n_i)} \qquad n_i = 2, 3, ...nb_{tot} \tag{5}$$

2.4. Load balancing (lb)

The load-balancing function is given in Eq. (6).

$$lb = \sum_{i=1}^{m} \left(\frac{I_{ni}}{I_{nj,avg}}\right) \tag{6}$$

$I_{nj,avg}$ can be calculated using Eq. (7).

$$I_{nj,avg} = \frac{1}{m}\sum_{j=1}^{m} I_{nj}, \tag{7}$$

where I_{ni} and I_{nj} are the currents of the associated branches.

3. Modified wavelet neural network

The use of wavelets has been popular in engineering problems recently, and they present an effective time-frequency solution of the analyzed signal. Furthermore, artificial neural networks (ANNs) are important due to their ability to model nonlinear systems in power distribution networks [34]. As of late, the concept of the WNN has been introduced. Although in theory it remains similar to the traditional ANN, the main difference is its use of activation neurons produced from mother wavelet functions. As in the case of the classical ANN, however, training and testing procedures remain the same. It has been reported that classification and estimation (regression analysis) can be performed more effectively with the WNN rather than the traditional ANN.

The network type can be defined in different types, but the structure of a feed-forward neural network is taken into account here and applied in order to estimate the optimal placing of capacitors and DGs. An advantage of using a WNN is having numerous wavelet functions in hidden layer(s), too.

Published papers demonstrate that some scholars have interpreted the use of WNNs from a different perspective. For this reason, the use of WNNs can be divided into two groups. The first one includes the wavelet decomposition of the analyzed signal and then the use of those approximation and detail coefficients as inputs of the predefined ANN structure. In this particular example, the ANN consists of well-known activation neurons such as tansig and logsig. However, the second one includes both an ANN and wavelet analysis. Activation neurons are mainly wavelet functions that can be selected from a large wavelet family. The second type reduces the number of used activation neurons, providing better regression analysis [35].

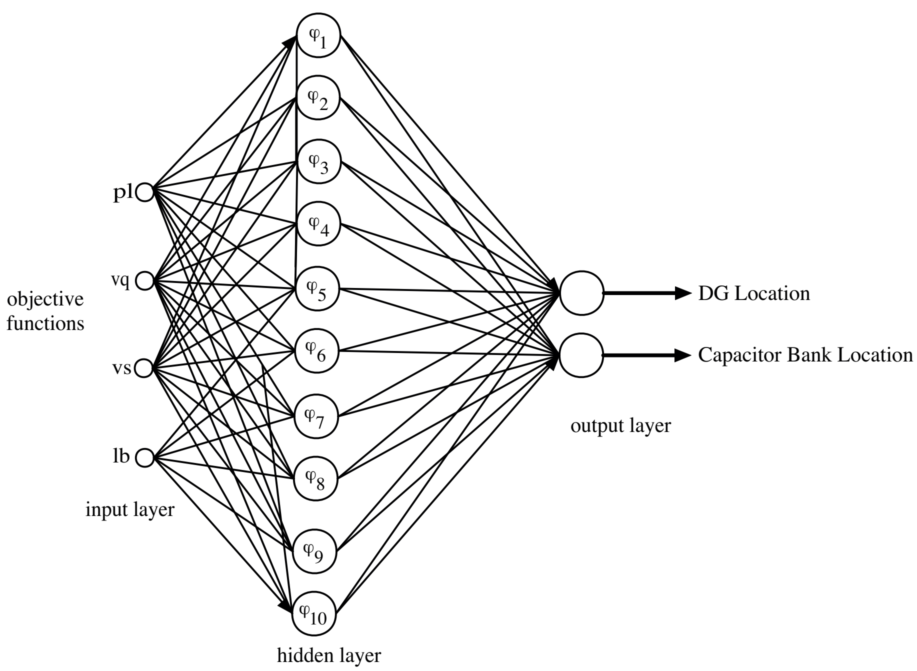

Figure 2. Wavelet-based neural network configuration.

In Figure 2, $\phi_1 ... \phi_{10}$ are the (optimized) wavelet-based activation neurons.

Although some scholars prefer to use the first one, the second type is used to estimate the optimal placing of capacitors and DGs on a power network under analysis in this work. Using the second type of network (WNN) results in the selection problem of a mother wavelet family over a large wavelet pool. Deciding on an optimum wavelet filter that proposes a high efficiency from a variety of filters requires additional work. This is simply remedied using an approach known as the minimum description length (MDL) data criterion. This approach helps not only select the most appropriate mother wavelet function (i.e. filter) but also to select the best wavelet filter number [36]. Once the best wavelet filter is chosen using MDL, the selected filter is used for the rest of the calculation.

Eq. (8) gives the definition of MDL method.

$$MDL(x,y) = \min\left(\frac{3}{2}x\log N + \frac{N}{2}\log\left\|\tilde{a}_y - a_y^x\right\|^2\right)$$

$$0 \le x < N; 1 \le y \le M \tag{8}$$

In Eq. (8), $a\tilde{a}_y = W_y f$ represents approximation coefficients using n wavelet filter and f decomposition coefficient. $a_y^x = \Theta^x W_y f$ represents approximation coefficients with a threshold function of Θ^x retaining m largest elements of $a\tilde{a}_y$, setting all other elements to zero. The length of the signal is N, the total number of wavelet filters is M, and x represents the wavelet coefficients. Details of the MDL approach can be found in the literature.

The selected wavelet filter using MDL for particular simulation data cannot be effectively applied to another simulation set. The optimum wavelet family is then decided according to the RMS/RMSE criteria. In this work, db2, sym3, coif4, bior3.7, and rbio4.4 wavelet filters are the best wavelet filters for the simulation data. After selecting the best wavelet filter, selecting the optimum decomposition level should be considered. For this purpose, Shannon entropy is applied to simulation data processed with the best wavelet filter. The decomposition level where the Shannon entropy curve changes its direction is regarded as the optimum level with a specific wavelet filter. After this level, it is not necessary to use the other decomposition levels.

4. Simulation results

In this paper, complex neural network architecture with wavelet-based neurons is used to simulate the relationship between an input and an output. When the function is learnt by the WNN, then the optimal capacity and position is predicted.

Training and testing data are produced in the MATLAB environment. As in the previous methods (GSS, GS, and AHM), loss reduction of active and reactive power and maximizing voltage profile are taken into account.

There are some concerns about the proposed objective functions that can be valid only in vertically integrated utilities from a power system perspective. Indeed, the cost of DG and the cost of capacitor can very seldom be added because private producers own DGs, while the distribution system operator pays for that. The stochastic behavior of DG (i.e. wind, solar) is not considered and the coincidence between load and generation is taken as a constant in the analysis.

Remarkably, four methods have been shown to produce similar results. Therefore, performance analysis only consists of computational burden and functionality.

4.1. GSS algorithm

In the GSS algorithm, the search space is decreased by checking some separate values of the capacitor size only in every computational step. The minimization of losses is regarded as an objective function. The main constraints are restraining the maximum capacitor size selected as total load size.

4.2. GS algorithm

In the GS algorithm, a shunt capacitor is added to each bus and the size of the capacitor is changed from 0%–100% of total connected load in small computational runs. Minimization of losses is regarded as the objective function. For this purpose, successive load flow methods are used for each capacitor size. The main constraints are to restrain the maximum capacitor size selected as total load size, as in the case of GSS.

4.3. AHM technique

In the AHM technique, a criterion known as loss sensitivity is formulated for optimum placing problems of capacitors and DGs. This method uses bus current and bus voltage matrices. The size of network plays an important role for this technique, due to matrix manipulations.

4.4. WNN technique

In the WNN technique, wavelet-type activation neurons are selected in layers and these neurons are optimized during the training procedure. Therefore, the computational speed is high in testing procedure. Moreover, there is no constraint or matrix calculation and it can be applied to large networks with high reliability. Figure 3 demonstrates the data flow through the individual components of WNN technique.

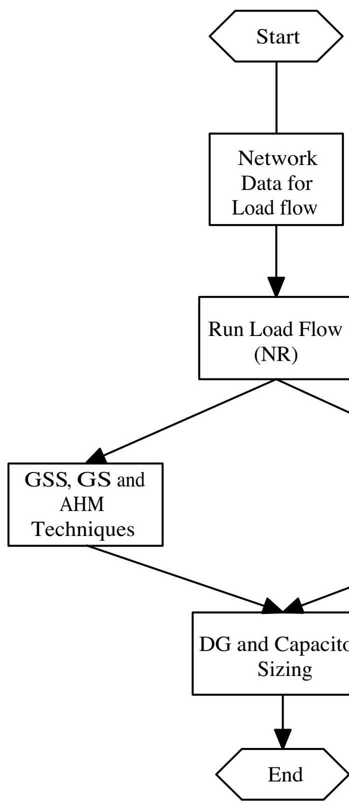

Figure 3. Flow diagram of the proposed DG and capacitor sizing/placing approach.

WNN method is then tested using six well-known IEEE buses, which are 12 bus, 12 bus + DG, 33 bus, and 33 bus + DG radial feeders. Their graphical examples can be found in the literature [37]. All objective functions, load values at buses, and total DG capacity are the inputs of the WNN. The output of the network serves to predict the active power of all PQ buses, the most critical bus, and the optimal bus for placing capacitors and DGs. The suggested network type consists only of one hidden layer with 10 neurons after the modification process of MDL and Shannon's entropy. As a performance criterion, RMSE is selected, and for both training and testing procedures it is calculated as 0.14 and 0.11, respectively. In training and testing procedures, the resilient back propagation algorithm is used, which is recorded faster than the standard steepest descent algorithm. The performances of WNN and the traditional techniques (GSS, GS, and AHM) can be seen in Tables 1 and 2. Graphical representations of the analyzed methods on the test feeders are given in Figures 4 and 5.

Table 1. DG placing for 12, 12 + DG, 33, and 33 + DG test bus feeders [38].

	Values /methods	Optimal bus	Optimal capacity (MV)	Active power loss without DG (MW)	Reactive power loss without DG (MVAr)	Active power loss with DG (MW)	Reactive power loss with DG (MVAr)	Min woltage without DG	Min voltage with DG
DC placing for 12	GSS	9	0.2354	0.02069	0.00806	0.01076	0.00413	0.9433 pu at bus 12	0.9835 pu at bus 7
	GS	9	0.2349	0.02069	0.00806	0.01076	0.00414	0.9433 pu at bus 12	0.9834 pu at bus 7
	AHM	9	0.2271	0.02069	0.00806	0.01077	0.00415	0.9433 pu at bus 12	0.9823 pu at bus 12
	WNN	9	0.2386	0.02069	0.00806	0.01077	0.00415	0.9433 pu at bus 12	0.9842 pu at bus 12
DC placing for 12 + DG	GSS	8	0.2042	0.01119	0.0047	0.00683	0.00282	0.9594 pu at bus 11	0.984 pu at bus 11
	GS	8	0.2044	0.01119	0.0047	0.00683	0.00262	0.9594 pu at bus 11	0.984 pu at bus 11
	AHM	9	0.2276	0.01199	0.0047	0.00746	0.00279	0.9433 pu at bus 12	0.9917 pu at bus 7
	WNN	8	0.2251	0.01199	0.0047	0.0094	0.0025	0.9557 pu at bus 11	0.9916 pu at bus 11
DC placing for 33	GSS	6	2.5902	0.211	0.143	0.111	0.00816	0.9037 pu at bus 18	0.9423 pu at bus 18
	GS	6	2.6005	0.211	0.143	0.111	0.00817	0.9037 pu at bus 18	0.9425 pu at bus 18
	AHM	6	2.4907	0.2111	0.143	0.111	0.00816	0.9037 pu at bus 18	0.409 pu at bus 18
	WNN	6	2.5645	0.2112	0.143	0.111	0.00415	0.903 pu at bus 18	0.9444 pu at bus 18
DC placing for 33 + DG	GSS	29	1.3379	0.1335	0.0919	0.0768	0.0552	0.9283 pu at bus 33	0.9633 pu at bus 14
	GS	29	1.3335	0.1335	0.0919	0.0768	0.0552	0.9283 pu at bus 33	0.9633 pu at bus 14
	AHM	6	2.4462	0.1335	0.0919	0.0825	0.006	0.9283 pu at bus 33	0.9639 pu at bus 33
	WNN	29	1.7081	0.1333	0.0918	0.077	0.0557	0.928 pu at bus 33	0.9635 pu at bus 14

It can be observed from Figures 4 and 5 that the performance of WNN technique with respect to optimal DG capacities is close to the performances of other techniques.

5. Conclusion

Optimal operation of distribution systems has garnered attention due to technical, economical, and environmental aspects. To achieve this, two major problems need to be solved, i.e. optimal capacitor and DG placement.

Table 2. Capacitor placing for 12, 12 + DG, 33, and 33 + DG test bus feeders [38].

	Values /methods	Optimal bus	Optimal capacity (MVAr)	Active power loss without capacitor (MW)	Reactive power loss without capacitor (MVAr)	Active power loss with capacitor (MW)	Reactive power loss with capacitor (MVAr)	Min voltage without capacitor	Min voltage with capacitor
Capacitor placing for 12	GSS	9	0.2101	0.02069	0.00806	0.01257	0.00483	0.9433 pu at bus 12	0.9563 pu at bus 7
	GS	9	0.2106	0.02069	0.00806	0.01257	0.00483	0.9433 pu at bus 12	0.9563 pu at bus 7
	AHM	9	0.2102	0.02069	0.00806	0.01257	0.00483	0.9433 pu at bus 12	0.9563 pu at bus 12
	WNN	9	0.2143	0.02069	0.00806	0.01257	0.00483	0.9433 pu at bus 12	0.9563 pu at bus 12
Capacitor placing for 12 + DG	GSS	8	0.2042	0.01199	0.0047	0.00677	0.00259	0.9594 pu at bus 11	0.9688 pu at bus 11
	GS	8	0.2025	0.01199	0.0047	0.00677	0.00259	0.9594 pu at bus 11	0.9687 pu at bus 11
	AHM	8	0.2105	0.0119	0.0047	0.00718	0.0027	0.9433 pu at bus 11	0.9719 pu at bus 11
	WNN	8	0.2077	0.01199	0.00472	0.0079	0.0026	0.9557 pu at bus 11	0.9735 pu at bus 11
Capacitor placing for 33	GSS	30	1.258	0.211	0.143	0.1513	0.1038	0.9037 pu at bus 18	0.9164 pu at bus 18
	GS	30	1.265	0.211	0.143	0.1513	0.1038	0.9037 pu at bus 12	0.9165 pu at bus 12
	AHM	30	1.2297	0.211	0.143	0.1514	0.1037	0.9037 pu at bus 18	0.9162 pu at bus 18
	WNN	30	1.259	0.211	0.1431	0.1513	0.1037	0.9036 pu at bus 18	0.9163 pu at bus 18
Capacitor placing for 33 + DG	GSS	30	1.1334	0.1335	0.0919	0.0867	0.0604	0.9283 pu at bus 33	0.9548 pu at bus 14
	GS	30	1.127	0.1335	0.0919	0.0867	0.0604	0.9283 pu at bus 33	0.9547 pu at bus 14
	AHM	30	1.2244	0.1335	0.0919	0.087	0.0607	0.9283 pu at bus 33	0.9553 pu at bus 14
	WNN	30	1.1704	0.1333	0.091	0.087	0.0605	0.928 pu at bus 33	0.9549 pu at bus 14

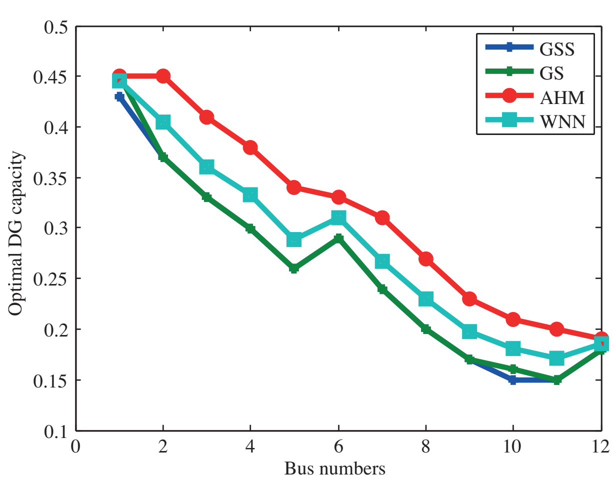

Figure 4. Optimal placement of DG at 12 bus + DG test feeder [38].

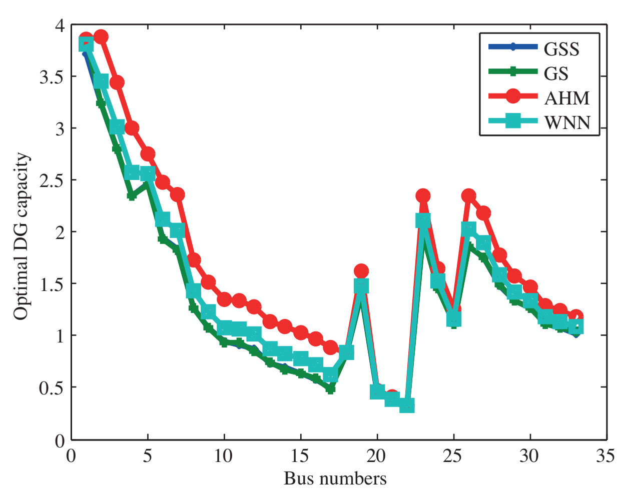

Figure 5. Optimal placement of DG at 33 bus + DG test feeder [38].

The optimal placement of capacitors and DGs will help the distribution network control reactive power, reduce losses, and increase voltage and frequency stability over the distribution network. For this purpose, WNN is suggested for the optimal location problem. It has also been compared to traditional methods, such as GSS, GS, and AHM. WNN presents an effective optimization method that is simple to implement for any radial bus system. The proposed technique can easily be applied to any distribution system, including different objective functions and different stability indices.

Acknowledgments

The authors are thankful to TÜBİTAK for its 2219 support to the University of Nottingham, UK, in 2013.

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