Improving the Conditions in a Radial Distribution Feeder by Implementing Distributed Generation

Original Scientific Paper

Marko Vukobratović
J. J. Strossmayer University of Osijek,
Faculty of Electrical Engineering,
Department of Power Engineering
Kneza Trpimira 2b, Osijek, Croatia
vukobratovic@etfos.hr

Srete Nikolovski
J. J. Strossmayer University of Osijek,
Faculty of Electrical Engineering,
Department of Power Engineering
Kneza Trpimira 2b, Osijek, Croatia
srete@etfos.hr

Predrag Marić
J. J. Strossmayer University of Osijek,
Faculty of Electrical Engineering,
Department of Power Engineering
Kneza Trpimira 2b, Osijek, Croatia
predrag.maric@etfos.hr

Abstract – *Distribution feeder is the final stage in the delivery of electricity to consumers. The feeder can be radial or networked. Radial feeders leave the power station towards the consumers without any connection to other power supply. Networked feeders have multiple connections to other supply points. It is common for long radial feeders for voltage to drop along the way and for losses to increase with increasing consumer's power or the number of consumers. In order to minimize feeder losses and improve voltage profile distributed generation (DG) can be implemented. It is important to define the optimal location and power of distributed generation in a specific feeder to obtain its maximum potential benefits. This paper presents a solution for optimal DG placement by selecting the right terminal and power of DG using the Genetic Algorithm (GA) and the Artificial Neural Network (ANN) hybrid method. The method is tested on a part of Croatian distribution network and verified by DIgSILENT PowerFactory software and the analytical approach. The results and comparison thereof and presented in clear and legible form.*

Keywords – *artificial neural network, distribution feeder, distributed generation, genetic algorithm.*

1. INTRODUCTION

Distributed generation (DG) changes the distribution network which, when DG is included, becomes an active load network resulting in changes of the power flow. Current-voltage conditions are now dependent on not only the consumers and their consumption, but also on the amount of power produced by DG. If selected properly and sized correctly, DG can improve electrical conditions, such as voltage, loss reduction, relieved transmission and distribution congestion, improved utility system reliability and power quality in the distribution network, [1].

Power flow analysis can provide a good designation of influence of each and every DG in the power system. Since small DGs mostly come from intermittent sources, it becomes necessary to implement an advanced management system for the power distribution network because repetitive power flow calculations could be resource and time consuming. Accordingly, it is necessary to develop mathematical optimization models that can be implemented in the management system developed for the power distribution network [2].

This paper is logically divided into three parts organized in five main chapters. Section 1 briefly describes the optimization problem and presents the mathematical framework. An artificial neural network (ANN) is described in Section 2 in which the process of loss estimation by ANN is also presented. The semi-hybrid method consisting of an ANN and the Genetic Algorithm (GA) is shown in Section 3. Finally, Section 4 presents optimization results and improvements made to the distribution network. Section 5 sums up contents of the aforementioned sections.

2. PROBLEM FORMULATION

The optimization problem can be described by a structure of an objective function supplemented by various restrictions [2]:

$$Min\, f(x,u),$$

such that

$$g(x,u)=0\ , \tag{1}$$

$$h(x,u)\leq 0\ , \tag{2}$$

where vector *u* is a vector of control variables, *x* is a vector of state variables, scalar *f(x)* is the objective function, while restrictions are given by the system of equation *g(x, u)* and inequalities *h(x,u)* [2].

The main goal of the proposed method is to determine the best location or multiple locations in the distribution power system for adequate distributed generation by minimizing different functions related to research goals, which are:

1. Reduction of active power losses in the observed power system, and
2. Voltage profile improvement in the observed radial feeder.

As the two above conditions are often inversely proportional to each other, there is a golden mean which represents the ideal optimal solution.

2.1. OBJECTIVE FUNCTION AND CONSTRAINTS

The main objective function could be described as follows:

$$F = Min P_{losses}\ , \tag{3}$$

where P_{losses} are losses of active power in the observed distribution power system.

The objective function of active power loss minimization is not sufficiently suitable without technical restrictions and a correct formulation of optimization constraints and could lead to wrong conclusions if the latter had not been accepted [2].

Optimal placement of distributed generation and the installed power solution provided with the proposed scientific method must be realistic and should not produce negative impacts on other system aspects such as voltage profile, demand response and power system reliability indicators. Constraints which need to be considered in the optimization process are active power constraints, reactive power constraints, apparent power through each branch constraints, voltage level constraints and constraints of reactive power generation in DG [1, 2, 4].

3. ARTIFICIAL NEURAL NETWORK DESIGN AND IMPLEMENTATION

In this paper, an artificial neural network (ANN) is developed in order to bypass a large number of iterative power flow calculations in a radial distribution network. An ANN replaces numerical and analytical calculations with a very good assessment. The main advantage of using the ANN lies in the speed of execution.

A typical back-propagation network, as evident in available literature, has an input layer, an output layer, and at least one hidden layer. The numbers of hidden layers are theoretically infinite but usually one to ten layers is adequate to solve any kind of complex problems [4].

Determining the correct number of neurons in the hidden layer is crucial for proper behavior of the ANN as a system which can be described as a transfer function *G(s)* with multiple inputs and outputs:

$$y(k) = F\left(\sum_{i=0}^{m} w_i(k) \times x_i(k) + b\right)\ , \tag{4}$$

where *y (k)* is an output value in discrete time *k*, *F* is a transfer function, w_i is a weight factor value where *i* can have any value between *0* and *m*, x_i represents the input value where *i* can have any value between *0* and *m* and *b* is bias.

The exact number of hidden neurons can be best determined empirically, but it is an unwritten rule that the number can be determined by the following equation [5]:

$$\boldsymbol{N_h} = \frac{\boldsymbol{N_{samples}}}{[\boldsymbol{k}\times(\boldsymbol{N_{input}}\times\boldsymbol{N_{output}})]}, \tag{5}$$

where N_h, N_s, N_{input}, N_{output}, and *k* are the number of hidden neurons, a known number of samples for training, a known number of input neurons, a known number of output neurons, and an arbitrary factor that is determined empirically, respectively.

The training data for the ANN consists of results of loss calculation for various DG active power production. In creating training data DG active power is changed in multiple operation scenarios from 0 kW (which represents a power distribution system with no DG production) to 1.350kW (excessive production by technical limits of the observed generator) in 10kW increments. Additionally, the voltage level on the low-voltage side and the voltage level on the medium-voltage side, given in per-unit (p.u.) values, and the injected current from DG production, given in kA, are discussed and observed for each operation scenario. Target data for ANN training are total radial feeder losses for each operation scenario connected to nine hidden layer neurons.

This particular feed-forward ANN with four input neurons, nine hidden neurons and one output neuron can be described by the following equations:

$$\begin{aligned}
m_1 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b1)\\
m_2 &= F_2(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b2)\\
m_3 &= F_3(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b3)\\
m_4 &= F_4(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b4)\\
m_5 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b5)\quad ,\\
m_6 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b6)\\
m_7 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b7)\\
m_8 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b8)\\
m_9 &= F_1(q_1n_1 + q_2n_2 + q_3n_3 + q_4n_4 + b9)
\end{aligned} \tag{6}$$

where m_1 to m_9 represent values of hidden neurons focused towards the output layer, F_1 *and* F_2 represent transfer functions, q_1 to q_4 represent weight factor values of four input neurons and n_1 to n_4 represent transfer function values of input neurons.

The output value y is then determined by:

$$y = F_0(r_1m_1 + r_2m_2 + \ldots + r_9m_9 + b_o), \tag{7}$$

where F_o represents the transfer function of the output neuron, r_1 to r_9 represent weight factor values of neuron connections from nine hidden neurons to output neuron, and m_1 to m_2 represent values provided by nine hidden neurons and their transfer functions, respectively.

The results of each operation scenario are represented in tables. Power losses in the electrical network can be computed by means of load flow simulation generated in DIgSILENT PowerFactory software. Those results can be used to control results provided by the ANN. Quantification and determination of power losses are essential due to the impact on the power system economic operation and the lifetime of the included equipment [6]. Performance of ANN training is shown in Fig. 1.

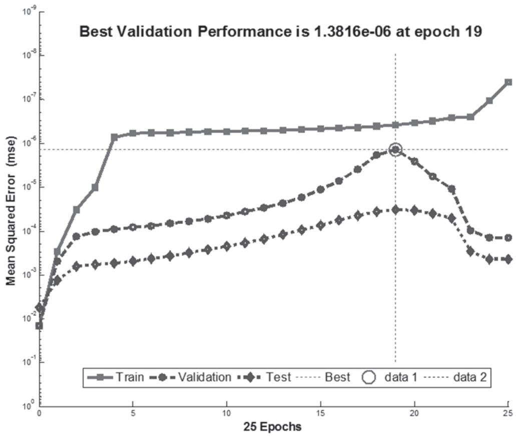

Fig. 1. Performance diagram of ANN training

For the purpose of electrical network modelling, data is obtained from the Croatian national grid company "HEP-ODS Elektroslavonija" for part of the distribution network with the nominal voltage of 35(20)kV and 0.4 kV with 48 terminals, 23 transformers and 25 semi-different low-voltage loads. The distribution network is connected to the transmission network on two sides, but it is never doubly fed due to operator technical conditions. If it is fully loaded, doubly-fed, the voltage drops under 0.89 p.u.

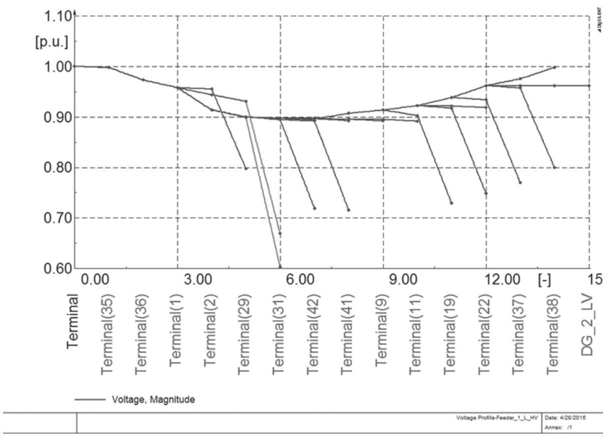

Fig. 2. Voltage values on terminals in a fully loaded distribution network

3.1. LOSS ESTIMATION BY ANN

The ANN is modelled in MATLAB software. After the procedure of ANN training is finished, a graph representing how the results given by the ANN correspond to the control variables and results provided by DIgSILENT PowerFactory, can be created, as shown in Fig. 3.

The results provided by DIgSILENT PowerFactory power flow calculation are taken as correct real-life values since this software has previously and frequently proven its reliability and precision [2]. Results provided by the ANN are accurate only in single-fed scenarios with static consumption models. In doubly-fed network types and with variable consumers, the ANN cannot provide an accurate enough solution in all cases. This provides a good basis for further research. The ANN is first tested on one terminal which is randomly selected for DG connection. The behavior of ANN estimation is precise and accurate, regardless of which number of implementation terminals and DG power it is tested on as long as it is a single-fed feeder with static consumers.

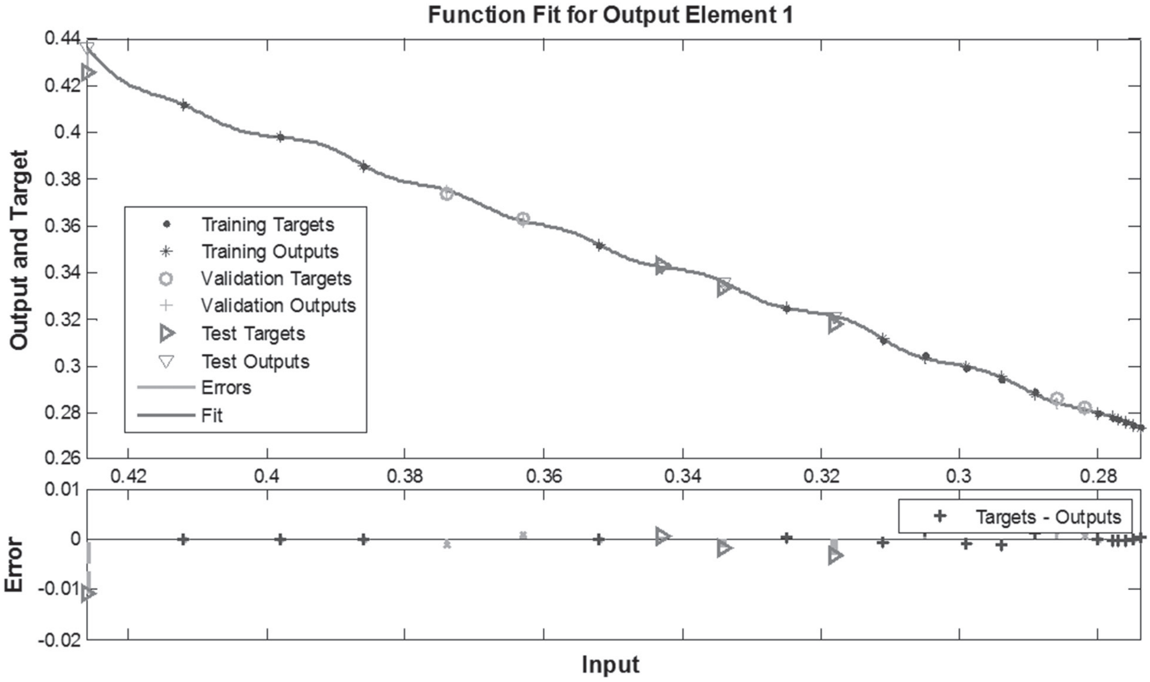

Fig. 3. Fitting of the ANN

By running the ANN on a set of variables for a selected terminal and running the power flow calculation in DIgSILENT PowerFactory software with the same DG values, results can be compared and evaluated. The performance of the ANN is acceptable; the comparison of results given by DIgSILENT PowerFactory and the ANN after proper training shows that the ANN manages to determine the valid value of power losses in a single-fed feeder with static consumers. The ANN results are generally matching results provided by DIgSILENT PowerFactory. Furthermore, additional training data from various types of operating scenarios could be useful if improved precision were an objective.

4. GENETIC ALGORITHM AND ANN HYBRID METHOD

Coding of parameters optimised and coding of results has to be a fixed-length bit string record in order for GA to function properly. Each position in a string represents a particular feature of an individual solution, i.e., power or location of submitted DG. The value stored in that particular position shows how one feature is evaluated in the solution. In specific requirements, for the purpose of research, operation scenarios are divided by the power of implemented DG and by the position of the connected terminal. The arrangement of operation scenarios in the number of population can be determined in several ways, as presented by Alinejad-Beromi et al. [4] and Abour El-Ela et al. [6]. The authors of this paper used DG power as a difference from each population which implies that the number of population is equal to the number of different power possibilities. Individuals in each population differ from each other by the number of terminals on which they are connected to the distribution network. The proposed method is represented by the algorithm shown in Fig. 4; it uses the GA and the ANN to find the best solution.

4.1. LOAD MODEL

The total installed peak power demand in the observed distribution system is 2.59MVA with an average power factor of 0.92-0.95. The conditions considered by this research are a peak loaded network with a load diversity factor of one (static consumers). Simulation and performance evaluation of the proposed method has been conducted for time-independent loads and time-independent generation. Since the modeled system is part of the Croatian National Grid Company "HEP-ODS Elektroslavonija" with mostly domestic consumers, there are no conditions of uninterrupted supply other than those given by the legal framework of the Republic of Croatia.

4.2. DISTRIBUTED GENERATION

There are different types of DG differed by their energy source and time-dependent production, [6]. In this paper, DG is modelled as a PQ node, with a power factor of cos φ = 1, and power that can vary from 100kW to 1350kW. The selected type of DG is based on a real type of generator widely used in distributed production worldwide. For the purpose of this model, Stamford generator with nominal power of 1350kW, 1500 min^{-1} is chosen, as part of a GE Gas Engine solution.

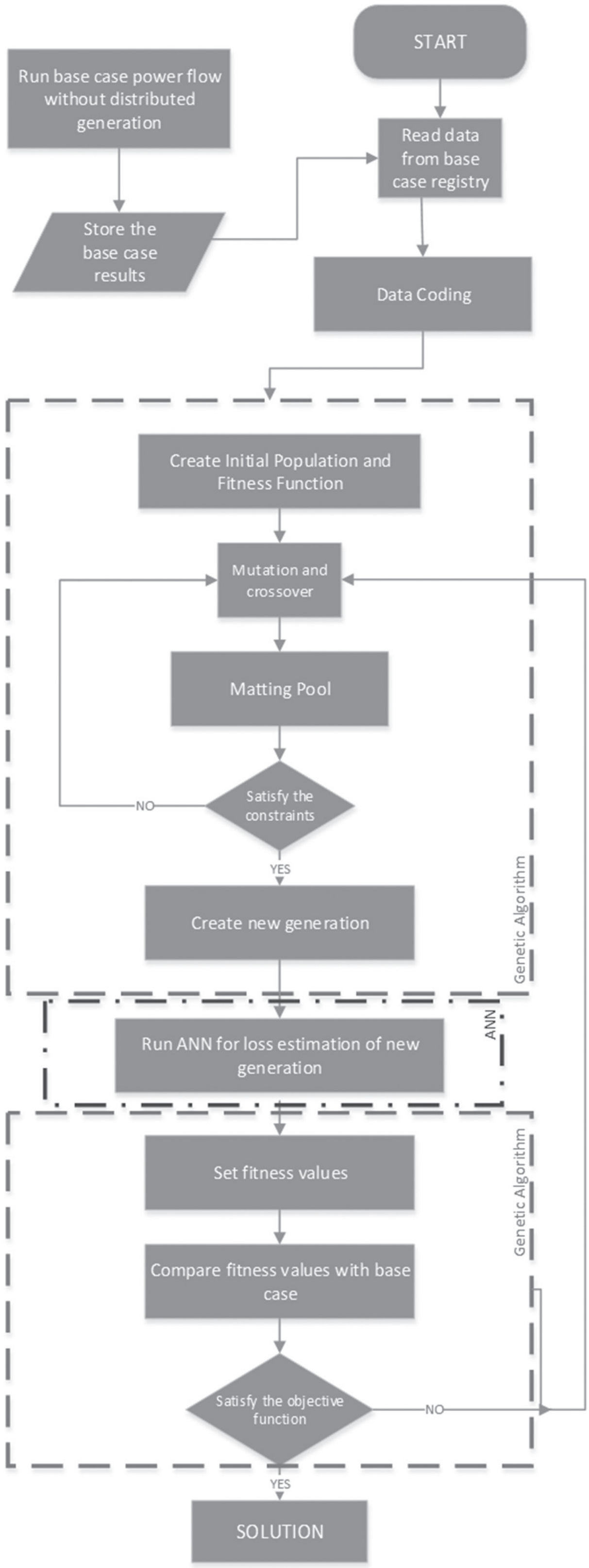

Fig. 4. The proposed method represented by the basic algorithm

5. PERFORMANCE EVALUATION AND RESULTS

Voltage profile in the observed distribution network after DG implementation is shown in Fig. 5. The lowest voltage level for this operation scenario was 0.95 p.u, and also regardless of the DG implementation terminal, the voltage level never exceeded the upper technical limit of 1.1 p.u.

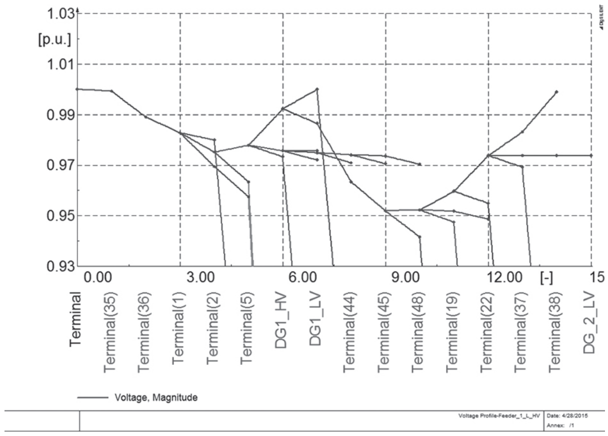

Fig. 5. Voltage values on terminals with DG

Optimization results obtained by means of the GA clearly indicate the global minimum of the values set, as shown in Fig. 6. The power of DG ranging from 1100kW to 1250kW causes the lowest level of total active power losses in the analyzed system and represents the best result of DG placement and power selection. This indicates the result with the lowest system losses, 1150kW DG on Terminal 8 located in the middle of the distribution feeder, on the fourth set of low-voltage terminals from 10 sets. A GE Gas Engine with Stamford generator is entirely capable of providing such power level. Total active power losses before installing DG in the distribution system were 468kW; after implementing DG on the designated terminal, total system losses were 274kW, or 41.4% lower.

The proposed solution provided by the GA and ANN method is evaluated with DIgSILENT PowerFactory software in order to check precision and accuracy of results. In accordance with these requirements, the generator is modelled in DIgSILENT PowerFactory on Terminal 8, with 1150kW installed power. Power flow calculation is performed for that operation scenario, and a significant improvement in active power losses reduction and regulation of voltage values on each terminal are observed and confirmed. Results given by the proposed method modelled in MATLAB and results provided by simulation in DIgSILENT PowerFactory correspond to strong similarity. This result confirms the opinion of the authors that the methods of soft computing can be successfully used in power system optimization with regard to the guidelines by which the chosen method is performed. The main advantage of using soft computing methods in power system optimization is the speed of execution and the possibility of avoiding many repetitive calculations.

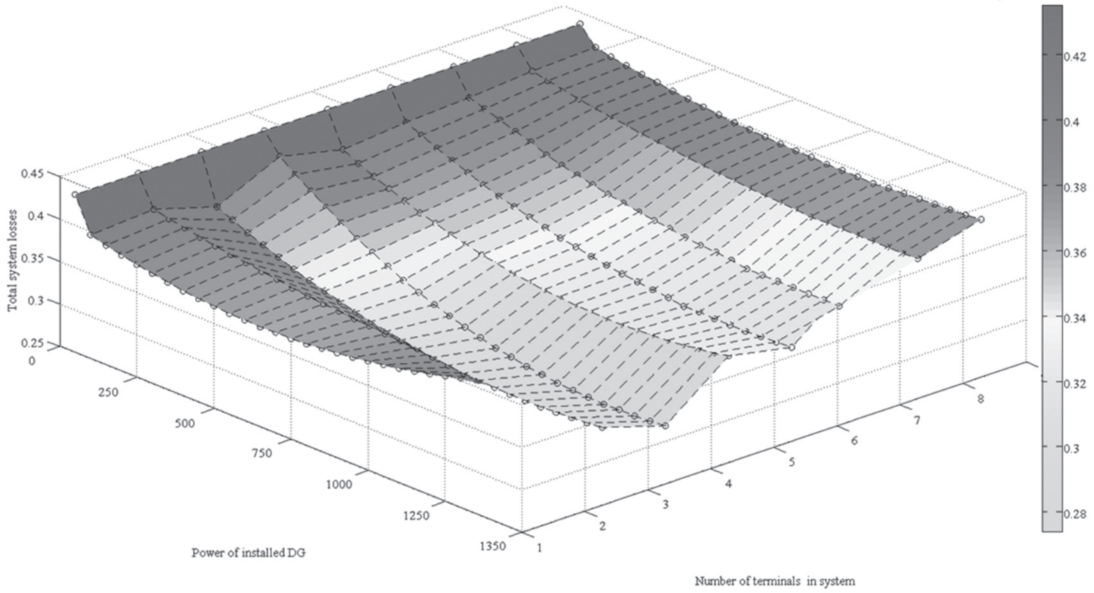

Fig. 6. Surface diagram of scenarios analysed by GA

6. CONCLUSION

An advanced optimization method based on Artificial Neural Networks (ANN) and Genetic Algorithms (GA) is proposed in this paper, and it is successfully demonstrated how the method could be used for determination of the size and location of DG. The process of power system optimization can be conducted by means of soft computing if guidelines for proper coding and recording of problems are followed. This method is based on formulation by an objective function and technical constraints. The quickly obtained correct solution for solving the given formulation is provided by using the ANN which is trained via power-flow calculation results provided by DIgSILENT PowerFactory software. The ANN proved to be fully functional for single-fed networks.

In addition, a GA is used for finding the best optimal solution, i.e., the one with the lowest active power losses, based on the best fitness performance of each individual in each population. Populations differ by the power of DG installed, and individuals differ by the number of terminals they are connected to.

Improvements in voltage profiles and active power losses reduction made by the proposed method confirm the usefulness of the combination of the ANN and the GA for providing fast and accurate enough optimization solutions in radial distribution systems. Results obtained in this paper make a good basis for further research which could be oriented to providing a new method for power system online management.

REFERENCES

[1] S. Biswas, S.K. Goswami, A. Chatterjee, "Optimum distributed generation placement with voltage sag effect minimization", Energy Conversion and Management, Vol. 53, No. 1, 2012, pp. 163-174.

[2] M. Vukobratović, P. Marić, Ž. Hederić, "Optimization Method for Control of Voltage Level and Active Power Losses Based on Optimal Distributed Generation Placement Using Artificial Neural Networks and Genetic Algorithms", Journal of Energy Technology, Vol. 6, No. 4, November 2013, pp. 1-10.

[3] D. Lukman, T.R. Blackburn, "Modified Algorithm of Load Flow Simulation for Loss Minimization in Power Systems", IEEE/PES, Sydney, 19-24 October 2003.

[4] Y. Alinejad-Beromi, M. Sedighizadeh, M.R. Bayat, M.E. Khodayar, "Using Genetic Algorithm for Distributed Generation Allocation to Reduce Losses and Improve Voltage Profile", International Universities Power Engineering Conference – UPEC, Brighton, 4-6 September 2007, pp. 954–959.

[5] M.T. Hagan, H.B. Demuth, M.H. Beale, O. de Jesus, "Neural Network Design, 2nd edition", Martin Hagan, September 2014.

[6] A.A. Abour El-Ela, S. M. Allam , M.M. Shatla, "Maximal Optimal Benefits of Distributed Generation using Genetic Algorithms", Electric Power System Research, Vol. 80, No. 7, 2010, pp. 869–877.

[7] M. Vardarajan, K.S. Swarup, "Differential Evolutionary Algorithm for Optimal Reactive Power Dispatch, Electric Power and Energy Systems", Vol. 30, No. 8, 2008, pp. 435–441.

[8] S.M. Moghaddas-Tafreshi, H.A. Zamani, S. M. Hakimi, "Optimal Sizing of Distributed Resources in

Micro Grid with Loss of Power Supply Probability Technology by Using Breeding Particle Swarm Optimization", J. Renewable Sustainable Energy, No. 3, pp. 1 -17, 2011.

[9] A.Q.H. Badar, B.S. Umre, A.S. Junghare, "Reactive Power Control using Dynamic Particle Swarm Optimization for Real Power Loss", Electric Power and Energy Systems, Vol. 41, No. 1, 2012, pp. 133–136.

[10] S. M. Hakimi, S. M. Moghaddas-Tafreshi, H. Hassanzadeh Fard, "Optimal Sizing of Reliable Hybrid Renewable Energy System Considered Various Load Type", J. Renewable Sustainable Energy, Vol. 3, No. 6, 2011, 062701.

[11] S.M. Moghaddas-Tafreshi, Elahe Mashhour, "Distributed Generation Modeling for Power Flow Studies and a Three-phase Unbalanced Power Flow Solution for Radial Distribution Systems Considering Distributed Generation", Electric Power Systems Research, Vol. 79, No. 4, 2009, pp. 680–686.

[12] W-S Tan, M.Y. Hassan, M.S. Majid, H.A. Rahman, "Optimal Distributed Renewable Generation Planning: a Review of Different Approaches", Renewable and Sustainable Energy Reviews, Vol. 18, February 2013, pp. 626–645.