Journal of Energy Technology

JET Volume 6 (2013), p.p. 11 - 30

Issue 4, November 2013

http://www.fe.um.si/sl/jet

OPTIMIZATION METHOD FOR CONTROL OF VOLTAGE LEVEL AND ACTIVE POWER LOSSES BASED ON OPTIMAL DISTRIBUTED GENERATION PLACEMENT USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

OPTIMIZACIJSKA METODA ZA NADZOR NAPETOSTNIH NIVOJEV IN IZGUB Z UPOŠTEVANJEM OPTIMALNE IMPLEMENTACIJE RAZPRŠENE PROIZVODNJE S POMOČJO NEVRONSKIH MREŽ IN GENETSKIH ALGORITMOV

Marko Vukobratović[ℜ], Predrag Marić, Željko Hederić

Keywords: distributed generation, Artificial Neural Network, Genetic Algorithm, voltage control

Abstract

This paper presents a method for reducing active power system losses and voltage level regulation by implementing adequate distributed generation capacity on the appropriate terminal in a distribution system. Active power losses are determined using an Artificial Neural Network (ANN) using simultaneous formulation for the determination process based on voltage level control and injected power. Adequate installed power of distributed generation and the appropriate terminal for distributed generation utilization are selected by means of a genetic

ℜ Corresponding author: Marko Vukobratović, Tel.: +385 31 224 656, Fax: +385 31 224 605, Mailing address: vukobratovic@etfos.hr

----

algorithm (GA), performed in a distinct manner that fits the type of decision-making assignment. The training data for Artificial Neural Network (ANN) is obtained by means of load flow simulation performed in DIgSILENT PowerFactory software on a part of the Croatian distribution network. The active power losses and voltage conditions are simulated for various operation scenarios in which the back propagation artificial neural network model has been tested to predict the power losses and voltage levels for each system terminal, and GA is used to determine the optimal terminal for distributed generation placement.

Povzetek

V članku je predstavljena metoda za zmanjšanje izgub v sistemu in regulacijo napetostnih nivojev z implementacijo razpršenih proizvodnih kapacitet na primernih terminalih distribucijskega sistema. Izgube delovne moči so določene z uporabo Umetne Nevronske Mreže (UNM), kjer je uporabljena sočasna formulacija v procesu odločanja na osnovi nadzora napetostnih nivojev in injiciranih moči. Ustrezne inštalirane moči razpršene proizvodnje in primerni terminali za izkoriščanje razpršene proizvodnje so izbrani na osnovi Genetskih Algoritmov (GA) izvedenih na poseben način, ki ustreza nalogam v procesu odločanja. Podatki za Umetno Nevronsko Mrežo so pridobljeni na osnovi simulacije pretoka energij v programskem paketu ''DIgSILENT PowerFactory'' na delu Hrvaškega distibucijskega omrežja. Simulacije izgub delovne moči in napetostnih razmer so izvedene za različne obratovalne scenarije, v katerih je testiran model ''vzratnega učenja'' umetne nevronske mreže za predvidevanje izgub moči in napetostnih nivojev za vsak sistemski terminal. Genetski algoritem je uporabljen za določitev optimalnega terminala za umestitev razpršene proizvodnje.

1 INTRODUCTION

The presence of distributed generation (DG) changes the load characteristics of the distribution network, which gradually becomes an active load network and implies changes in the power flow. Current-voltage conditions are now not only dependent on the current consumption but also on the production from DG. If sized and selected properly, DG can improve electrical conditions, such as improvement of voltage, loss reduction, relieved transmission and distribution congestion, improved utility system reliability and power quality in the distribution network, [1].

In order to determine the impact on the power system of each DG, it is necessary to perform the power flow analysis on a daily or hourly (or even 10-minute) basis. Due to the increased number of small DG, mostly from intermittent sources, it is necessary to implement an advanced management power distribution system to make the distribution network significantly automated. Accordingly, it is necessary to develop mathematical optimization models that can be implemented in the distribution network management system to enable optimal management. According to [2], an automated distribution network has to provide a fast and the accurate solution for power flow and current-voltage conditions control.

As an ideal solution, artificial neural networks (ANN) are imposed due to their ability to solve nonlinear problems in a short period of time, and if quality organized and made, they are able to perform real-time calculations necessary for the optimization of the distribution network. ANN have considerable potential in control systems because they can learn and adapt, they can approximate nonlinear functions, they are suited for parallel and distributed processing and model multivariable systems naturally, [3]. Since they are based on human experience and on

----

logical links between inputs and outputs, they can adopt various learning mechanisms and self-organization or training concepts, pattern recognition, forecasting etc.

ANN can be trained to generate control parameters for minimizing power losses and determining the optimal solution for DG implementation in the distribution network. This paper proposes an online real-time power flow optimization and voltage regulation method using ANN and a Genetic Algorithm (GA). ANN are highly robust and provide satisfactory solutions if provided with quality data and can dynamically determine the most appropriate DG solution by means of installed power and position in the system. The GA is used for solving constrained and constrained optimization problems and is based on a natural selection process that mimics biological evolution. The algorithm generates a population of individual solutions that are randomly selected from the population and used as parents for the next generation. Over several generations, the optimal population solution appears.

2 THE PROBLEM FORMULATION

Optimization problem can be generally shown with a model of the objective function and associated restrictions:

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

So that

$$\mathrm{g}(\mathrm{x,u})=0 \tag{2.1}$$

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

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).

The main goal of the proposed method is to determine the best locations in the distributed system for distributed generation by minimizing different functions related to project goals which are:

1. Reduction of active power losses
2. Voltage profile improvement

2.1 Objective function

The main objective function could be described as:

$$F = Min\, P_{losses} \tag{2.2}$$

Where P_{losses} are losses of active power in a system.

Minimization of active power losses is an essential requirement in a distribution system for efficient power system operation, [3]. Power losses can be calculated as:

$$P_{losses} = \sum_{i=1}^{N_B}\sum_{j=1}^{N_B} A_{ij}\left(P_i P_j + Q_i Q_j\right) + B_{ij}\left(Q_i P_j + P_i Q_j\right) \tag{2.3}$$

Where:

P, Q : real power and reactive power injection at respected terminal

N_B : terminal number

And $A_{i,j}$ $B_{i,j}$ are represented respectively:

$$B_{ij} = \frac{R_{ij}\sin(\delta_i - \delta_j)}{V_i V_j}, \quad A_{ij} = \frac{R_{ij}\cos(\delta_i - \delta_j)}{V_i V_j} \tag{2.4}$$

R_{ij} : line resistance between terminal i and terminal j

V, δ : voltage and load angle at the selected terminal

2.2 Constraints

The objective function of active power loss minimization is not sufficiently suitable without technical restrictions and correct formulation of optimization constraints. Optimal placement of distributed generation and the solution provided with the proposed method must be realistic and should not produce negative impacts on other system aspects. In order to achieve this goal, operational constraints should be properly evaluated and chosen, not only to enable proper operation of the proposed algorithm, but also to support the regular operation of the power system.

2.2.1 Power constraints

For the safe operation of the power system, the active power constraints are given by the expression:

$$P_{Gi} - P_{ti} - V_i \sum_{j=1}^{n} V_j \cdot \left(G_{ij}\sin(\theta_{ij}) + B_{ij}\sin(\theta_{ij})\right) \tag{2.5}$$

Where:

$i \in n$: number of nodes in network

P_{Gi} : active power production in node i

P_{ti} : active power consumption in node i

θ_{ij} : angle of mutual admittance $\overline{\overline{Y_{ij}}}$ of nodes i and j

G_{ij} : mutual conductance of nodes i and j

B_{ij} : mutual susceptance of nodes i and j

G_{ii} : self-conductance of node i

B_{ii} : self-susceptance of node i

Reactive power restrictions are given by the expression:

$$Q_{Gi} - Q_{ti} - V_i \sum_{j=1}^{n} V_j \cdot \left(G_{ij} \sin(\theta_{ij}) + B_{ij} \sin(\theta_{ij}) \right) \tag{2.6}$$

Where:

$i \in n$: number of nodes in network

Q_{Gi} : reactive power production in node i

Q_{ti} : reactive power consumption in node i

Besides active and reactive power constraints, the apparent power that is transmitted through each branch has to be below the physical limit of the branch transformer in steady-state operation. The constraint of apparent power is given by:

$$S_i \leq S_{i,\max} \tag{2.7}$$

Where:

S_i : apparent power in i[th] branch

$S_{i,\max}$: maximum allowed apparent power in i[th] branch

2.2.2 Voltage levels constraints

Voltage level restrictions are given by the expression:

$$V_{i-\min} \leq V_i \leq V_{i-\max} \tag{2.8}$$

Where:

$i \in n$: number of nodes in network

$V_{i-\min}$, $V_{i-\max}$: voltage limitations

V_i : voltage level in node i

2.2.3 Constraints of reactive power production in generator node

The generator has the capability curve and the technical operational limits, so the reactive power production is given by the expression:

$$Q_{Gi-\min} \le Q_{Gi} \le Q_{Gi-\max} \quad i \in \{N_{pv}, N_0\} \tag{2.9}$$

Where:

$Q_{Gi-\min}$, $Q_{Gi-\max}$: reactive power production limits in node i

N_{pv} : number of PV node

N_0 : node of DG

The objective function including the reduction of active power losses only could provide the solution without predicting a sufficient amount of reactive power reserves in case of the failure of one or more components in a power system. The appropriate optimization solution has to provide the optimization of voltage levels, voltage reduction, loss of stability risk and the reduction of power losses.

3 ARTIFICIAL NEURAL NETWORK DESIGN AND IMPLEMENTATION

Bearing in mind all restrictions and the objective of the optimization, a useful algorithm has to be developed. Because of the complexity and nonlinear interdependence of controlled variables, it is difficult to provide a fast and correct solution using classic (exact) optimization techniques, such as linear programming, the interior point method or mixed integer programming, [5]. ANN can be appropriate for solving such non-linear problems. There are several different types of ANN, including feed-forward neural network, radial basis function (RBF) network, Kohonen self-organizing network, recurrent neural network (RNN), bi-directional RNN, stochastic neural networks, etc. The appropriate neural network has to be properly selected since not every type of neural network will give the best solution for a certain problem. Back-propagation (BP) ANN can be used for the optimization problems since it meets the specific criteria: a flow chart of the problem can be described; there is a relatively easy way to generate a significant or at least necessary number of input and output examples; the problem appears to have considerable complexity but there is a clear solution; outputs may be unambiguous in some extreme cases.

The typical back-propagation network 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 four layers is adequate to solve any kind of complex problems.

Each layer has to be fully connected to the vicinal layer by every neuron, as shown in Figure 1.

The relationship between input and output values of multi-layer ANN can be represented as [6]:

$$y = f\left(\sum_{i=0}^{N-1} W_i \cdot X_i(t) - k\right) \tag{3.1}$$

Where:

y : output value

X_i : input value

W_i : weighting factor

k : threshold value

N : layer number

f : nonlinear function

When the network is created, the process of teaching has to be done in order to organize the neurons. This teaching makes usage of a learning rule, which is the variant of the Delta Rule, [3] The teaching starts with determining the error, which is the difference between the actual outputs and the desired outputs given in the training data. Based on this error, the weighting factor is changed in proportion to the error for the global accuracy. The algorithm for the weighting factor changing based on training data is, [6]:

$$\Delta_p W_{ji} = n\left(t_{pj} - o_{pj}\right) i_{pi} = n\delta_{pj}\, i_{pi} \tag{3.2}$$

Where:

n : learning rate

t_{pj} : j component of pth target output

o_{pj} : j component of pth computed output

i_{pi} : i component of pth input pattern

δ_{pj} : error of target and computed output

If well trained, an ANN can provide reasonable outputs for a new set of inputs enabling network training on a representative set of inputs with output correction. The training should be done on the largest possible set. Generally, the precision of ANN is increased by the larger training set with more input variables.

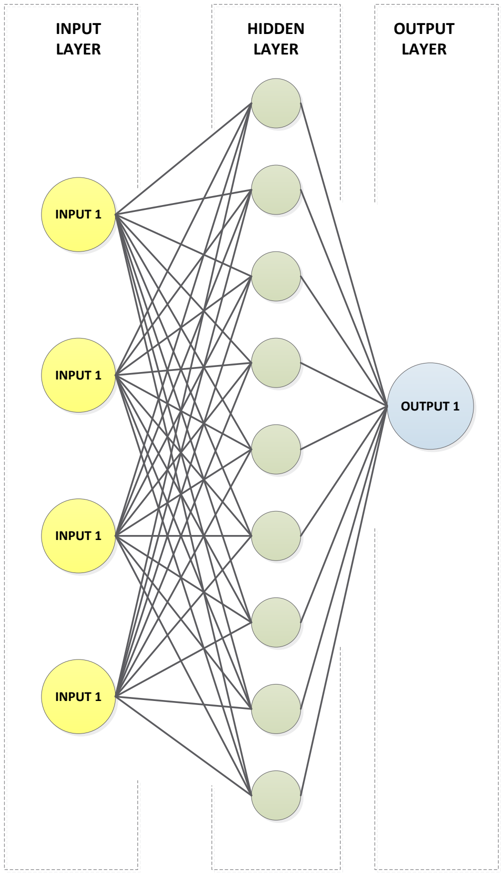

Figure 1: *Structure of Artificial Neural Network*

3.1 Neural network training

For the purpose of ANN training, a training data set has to be generated. Selecting the amount and type of training data is extremely important since the wrong selection could reduce the learning ability of the ANN or even provide an incorrect solution. For better accuracy, all dependent parameters have to be taken into account. The training data for the ANN consists of: DG active power production changed by operation scenarios from 0 kW (no production) to 1.350kW (excessive production) in 10kW increments, injected current from DG production given in kA, and the voltage level on the low-voltage side and the voltage level on the medium-voltage side, given in per-unit (p.u.) values. Targeted data for the ANN training are total feeder losses for each operation scenario. Accordingly, ANN has four input units and one output unit connected with nine hidden layer units.

The training is performed by the Levenberg-Marquardt algorithm for nonlinear least square problems, [7]. Calculations of each operation scenario for the training data generation are performed using DIgSILENT PowerFactory software, a leading power system analysis tool for applications in generation, transmission, distribution and industrial systems, [8]. The ANN is first trained on sample values for one terminal, and later it is tested on all proposed terminals.

The results of each operation scenario are introduced into tables. The power losses in the electrical network can be computed by means of load flow simulation generated in the DIgSILENT PowerFactory software. Quantification and determination of power losses is essential due to the impact on the power system economic operation and the lifetime of the included equipment, [9]. Performance of ANN training is shown in Figure 2.

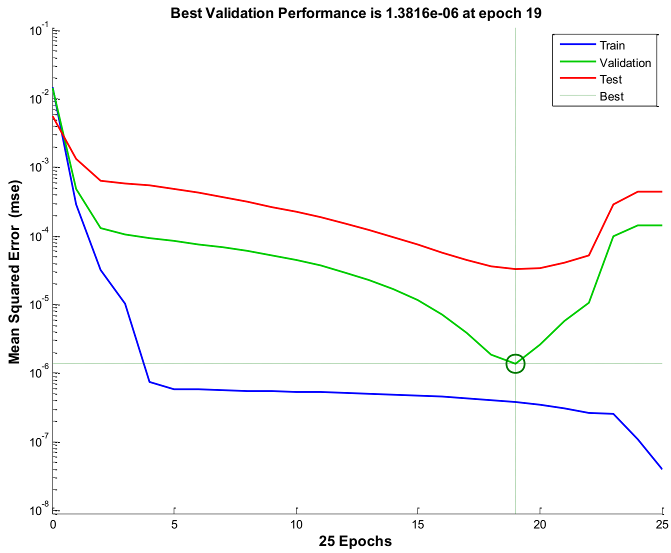

Figure 2: *Performance of ANN training*

For the purpose of electrical network modelling, data is obtained from the Croatian grid company HEP-ODS Elektroslavonija for a part of distribution network with a nominal voltage 35(20)kV and 0.4 kV with 48 terminals, 23 transformers and 25 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 fully loaded, the voltage drops under 0.89 p.u.

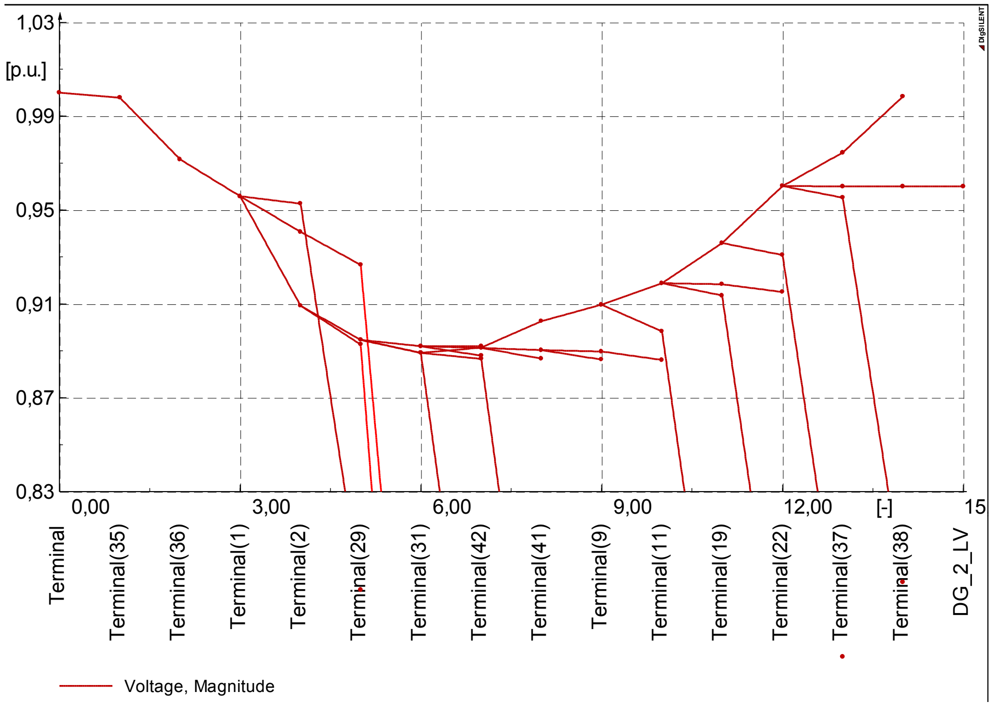

Figure 3: *Voltage values on terminals in fully loaded distribution network*

Of course, the normal operating conditions for this distribution network are not fully loaded terminals, and it is never doubly-fed, but it is necessary to observe what happens to voltage values. One possible solution for the increase of voltage values is planning for an adequate distributed generation on the convenient terminal in the system. In this case, the continuous electric power production would be as adequate a type as the stable source the network operator could rely on.

4 LOSSES ESTIMATION BY ANN

The ANN is modelled in MATLAB, which is a high-level language and interactive environment for numerical computation, visualization, and programming. After the ANN training, the fitting function and associated graph that shows how the results given by the ANN correspond to the control variables and results provided by DIgSILENT PowerFactory could be realized, as shown in Figure 4. 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.

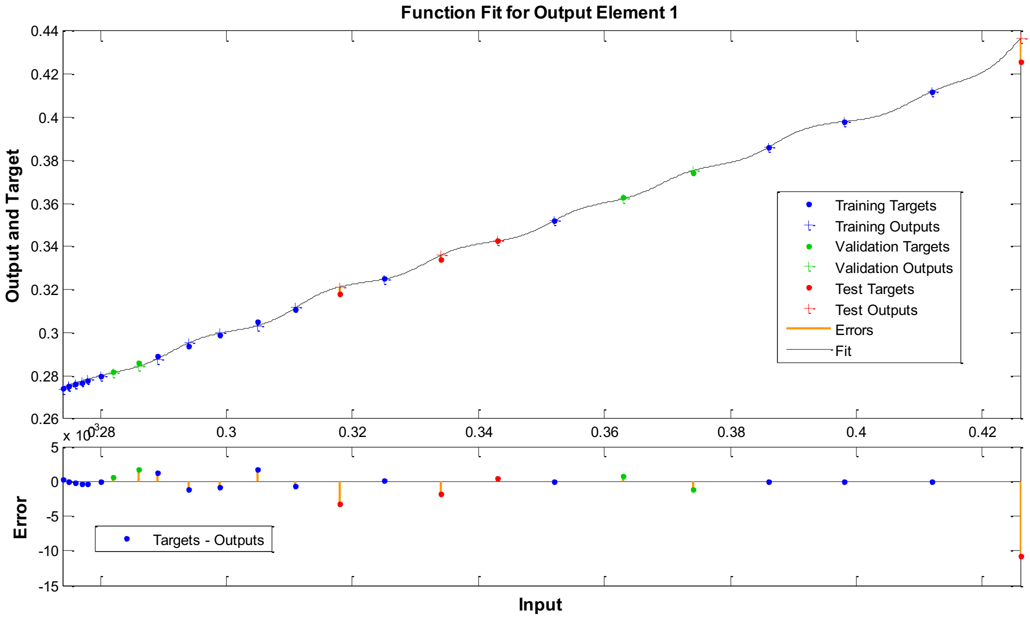

Figure 4: *Fitting of the ANN*

The ANN is first tested on one terminal, randomly selected for DG implementation. The output of the ANN estimation is precise and accurate, regardless of on which number of implementation terminals and DG power it is tested.

By running the ANN on a set of variables for a selected terminal and running the power flow calculation in DIgSILENT PowerFactory software with 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 by ANN after proper training shows that ANN manages to determine the valid value of power losses. The results of ANN are generally matching results provided by DIgSILENT PowerFactory. If the results should significantly deviate, the ANN has to be improved by managing the weight factors, biases and number of the hidden neurons. Furthermore, additional training data could be useful if improved precision would be a goal.

How the neural network response to input parameters can be shown by regression performance, as shown in Figure 5.

How the ANN estimates the influence on power losses and voltage control is shown in Table 1, where are shown compatible results of the calculation for one low voltage terminal, simultaneously made by ANN estimation and DIgSILENT calculation.

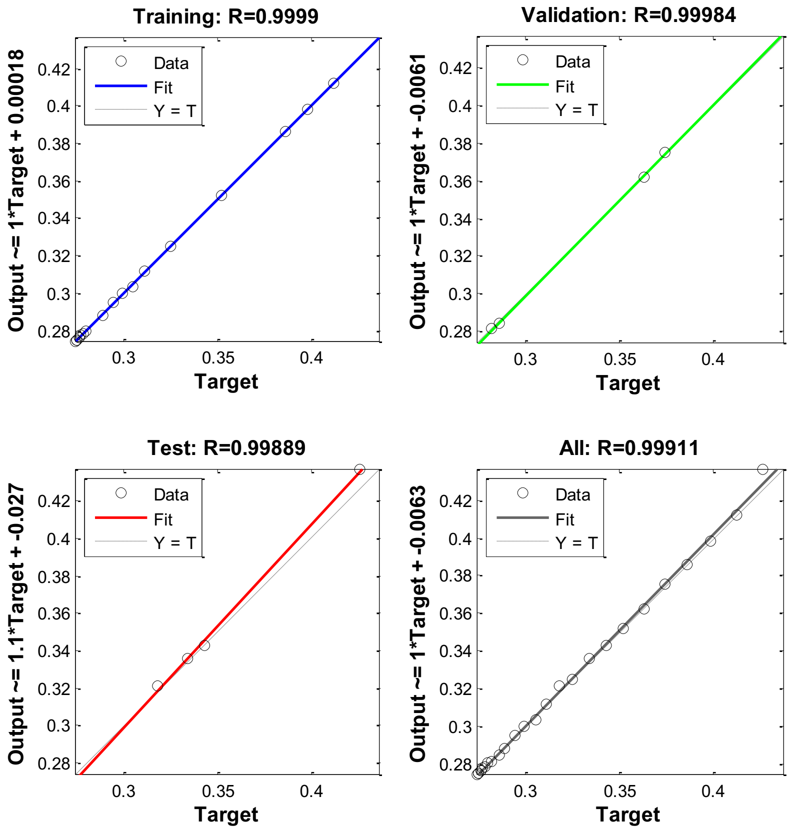

Figure 5: *Regression of the ANN*

The next step of determining the correct solution for minimizing active power losses and voltage level control is choosing the appropriate terminal and size of DG for implementation. This could be done analytically by comparing the results, by developing an additional ANN for decision making and choosing the correct terminal, or by developing a combined method that utilizes a genetic algorithm (GA) along with the ANN. In that case, the ANN is used for the assessment of the level of losses of the system, depending on the power of distributed generation and the terminal to which is it connected, and the GA is used to find the minimum solution.

Table 1: *Results of simulation in DIgSILENT and by ANN for one distributed generation terminal*

DG power productio n [kW]	Injected Current [kA]	Low Voltage Terminal [p.u.]	High Voltage Termin al [p.u.]	Active Power Losses [MW] **DIgSILENT**	Active Power Losses [MW] **ANN**
0,000	0.000	0.890	0.890	0.426	0.436788
100,000	1.481	1.000	0.975	0.412	0.411999

150,000	1.424	1.000	0.976	0.398	0.398002
200,000	1.374	1.000	0.977	0.386	0.385997
250,000	1.329	1.000	0.978	0.374	0.375231
300,000	1.291	1.000	0.978	0.363	0.36217
350,000	1.261	1.000	0.979	0.352	0.352026
400,000	1.238	1.000	0.980	0.343	0.342537
450,000	1.222	1.000	0.981	0.334	0.335857
500,000	1.214	1.000	0.982	0.325	0.324879
550,000	1.215	1.000	0.983	0.318	0.321286
600,000	1.222	1.000	0.984	0.311	0.31163
650,000	1.238	1.000	0.985	0.305	0.303296
700,000	1.260	1.000	0.986	0.299	0.299777
750,000	1.288	1.000	0.986	0.294	0.295214
800,000	1.323	1.000	0.987	0.289	0.287773
850,000	1.363	1.000	0.988	0.286	0.284287
900,000	1.408	1.000	0.989	0.282	0.281378
950,000	1.457	1.000	0.989	0.28	0.280029
1000,000	1.444	1.000	0.990	0.277	0.277324
1050,000	1.566	1.000	0.991	0.276	0.276195
1100,000	1.625	1.000	0.992	0.275	0.27499
1150,000	1.687	1.000	0.992	0.274	0.273763
1200,000	1.750	1.000	0.993	0.275	0.27499
1250,000	1.816	1.000	0.994	0.275	0.27499
1300,000	1.833	1.000	0.994	0.276	0.276195
1350,000	1.952	1.000	0.995	0.278	0.278344

4.1 Optimal solution finding

Once all the data for every desired terminal in the system is generated, the optimal solution must be found; doing so is a decision-making process that has to be properly designed. In recent years, increasing research efforts have been directed at applying ANN to decision-making tasks and mixed opinions about the value and performance of this technique have emerged: from considering ANN effective for unstructured decision making to categorically expressing reservations towards decisions made by artificial intelligence. The ANN for decision making and optimal solution finding is not used in this paper.

The genetic algorithm is becoming increasingly represented in optimization with non-linear dependences; it is an adaptive heuristic search algorithm introduced on the evolutionary themes of natural selection, [3]. In this case, the starting population could be that of potential (or all) terminals on which the selection would be performed. In such cases, the main condition that would need to be met is the well-defined fitness function of each terminal. [9]

Along with the GA, there are other types of soft-computing methods that could be used to find the best solution. Methods proven to be exceptionally good include Swarm Intelligence or Particle Swarm Optimization and Ant Colony Optimization, since they are efficient in the optimization of problems in a search space, [2]. Finally, the well-known Fuzzy Controller could be implemented, which could, if designed correctly, prove to be the most robust yet still simple design.

5 GENETIC ALGORITHM AND ANN HYBRID METHOD

Representation of results has to be a fixed-length bit string in order for GA to function. Each position in a string is assumed to represent a particular feature of an individual solution. The value stored in that particular position shows how one feature is evaluated in solution. In the specific requirements for the purpose of this paper, operation scenarios are divided by the power of implemented DG and by the number of connected terminals. The arrangement of operation scenarios in the number of the population can be determined in several ways. The authors of this paper used DG power as a difference from each population. Individuals in each population differ from each other by connected terminal.

The arrangement of the population and individual coding is shown on Figure 6.

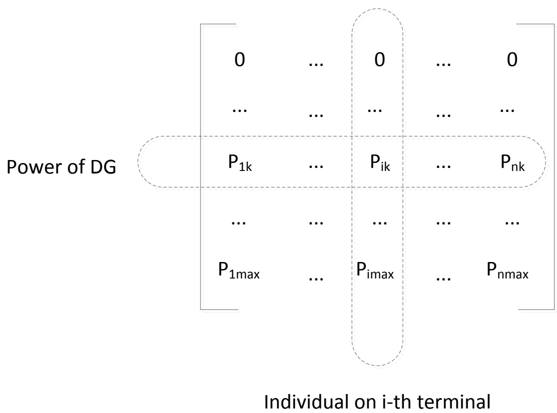

Figure 6: *Arrangement of population and individual coding*

For the purpose of future research, the task of developing a method that could utilize each terminal as a population, where individuals of that population are represented with different DG power, remains to be completed. The proposed method is represented by the algorithm shown on Figure 7; it uses GA and ANN to find the best solution.

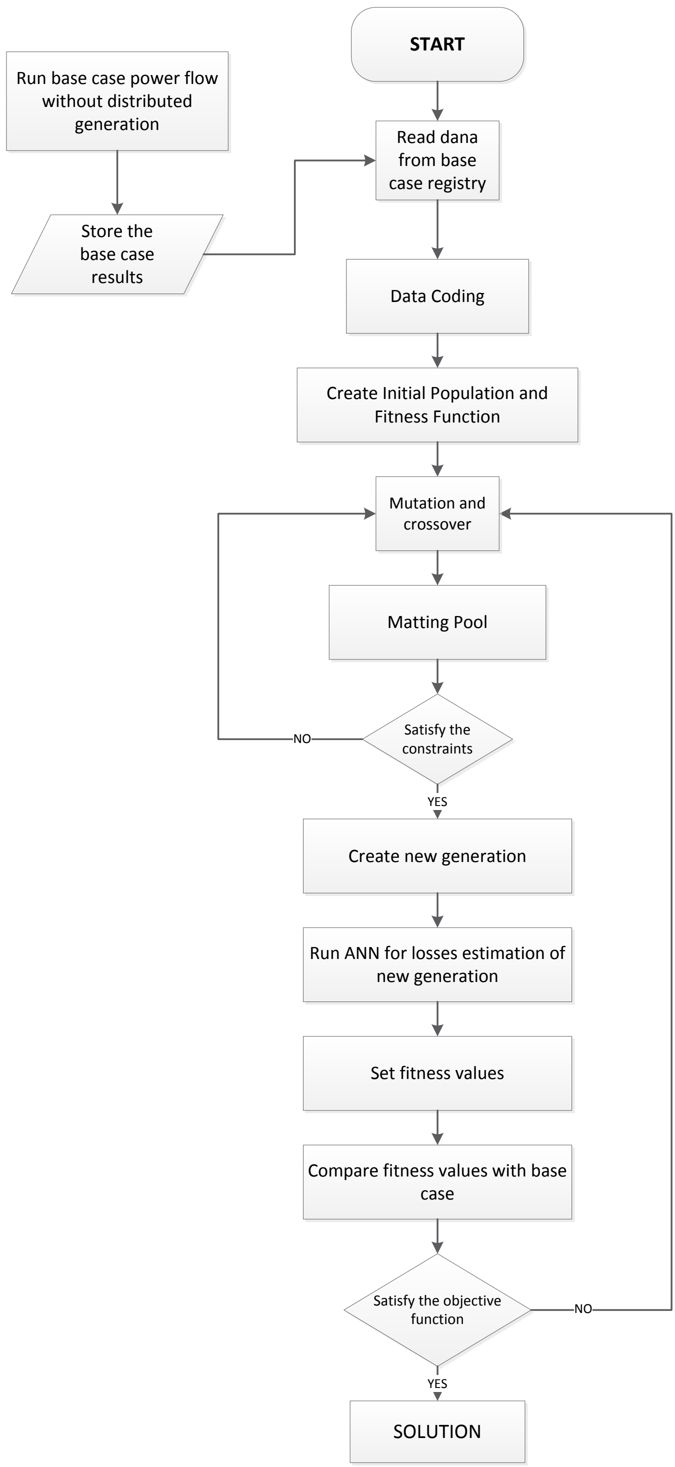

Figure 7: *Algorithm of proposed method*

----

6 THE METHOD APPLICATION IN DISTRIBUTION SYSTEM

6.1 System description

Figure 8 shows a 48-terminal system used for the purpose of modelling and testing of proposed methods. The network has the possibility of being doubly-fed, but the real operation conditions are usually two single-fed feeders. For the purpose of this paper, the worst case operation scenario is provided: a doubly-fed, fully-loaded distribution network. The constraints given in the previous chapter are fully satisfied in power flow calculation by DIgSILENT PowerFactory for every level of DG power.

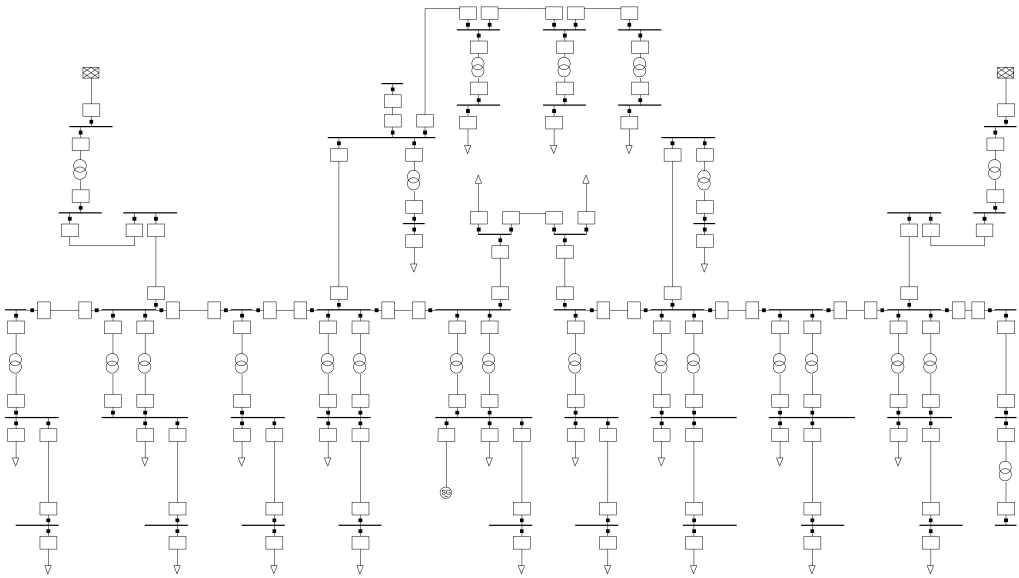

Figure 8: *Single line diagram of the 48-terminal distribution system considered*

6.2 Load model

The total installed peak power demand in the system is 2.59MVA with an average power factor of 0.9. The conditions considered by the research of this paper are peak loaded network with load diversity factor of one. The simulation and performance evaluation of the proposed method has been conducted for time-independent loads and time-independent generation.

6.3 Distributed generation

There are different types of DG, differed by their energy source and time-dependent production, [10]. 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, the Stamford generator with nominal power of 1350kW, 1500 min^{-1} is chosen, as a part of a GE Gas Engine solution.

6.4 Performance evaluation and results

Resulting simulations and all implemented calculations designed in the proposed algorithm can be represented with surface diagram shown in Figure 9.

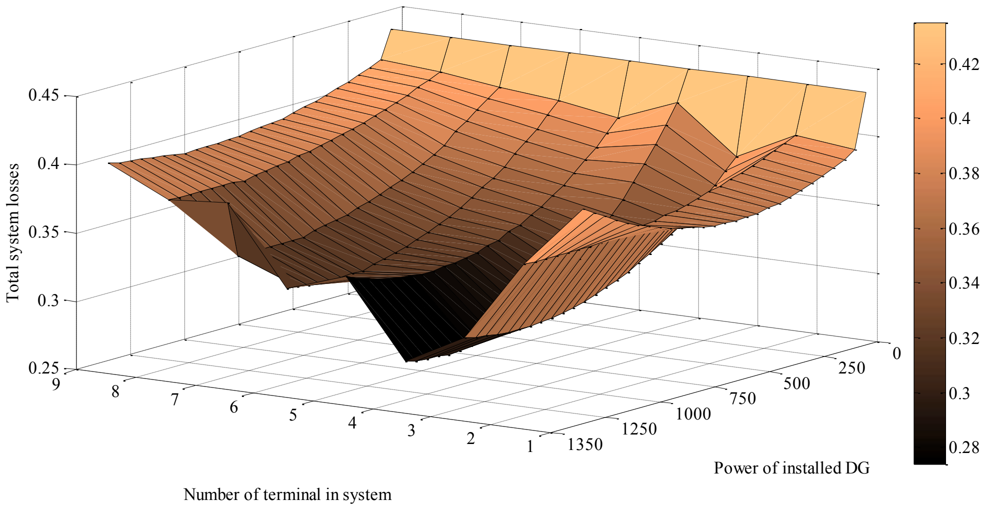

Figure 9: *Surface diagram of scenarios analysed by GA*

The surface diagram of results obtained via GA clearly indicates the global minimum of the values set. The dark area represents the set of optimal solutions according to the optimization formulation defined earlier in this paper. The power of DG from 1100kW to 1250kW causes the lowest level of total active power losses in the analysed system and 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 fifth set of low voltage terminals from 10 sets. A GE Gas Engine with Stamford generator is entirely capable of providing such a power level. Total active power losses before installing DG in the distribution system were 468kW; after implementing the DG on 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 the 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.

The voltage values in the modelled network have been improved significantly; the lowest voltage level for this operation scenario was 0.95 p.u, (Figure 10), but before DG

----

implementation the lowest voltage level was 0.88 p.u. Regardless of the DG implementation terminal, the voltage level never exceeded upper technical limit of 1.1 p.u.

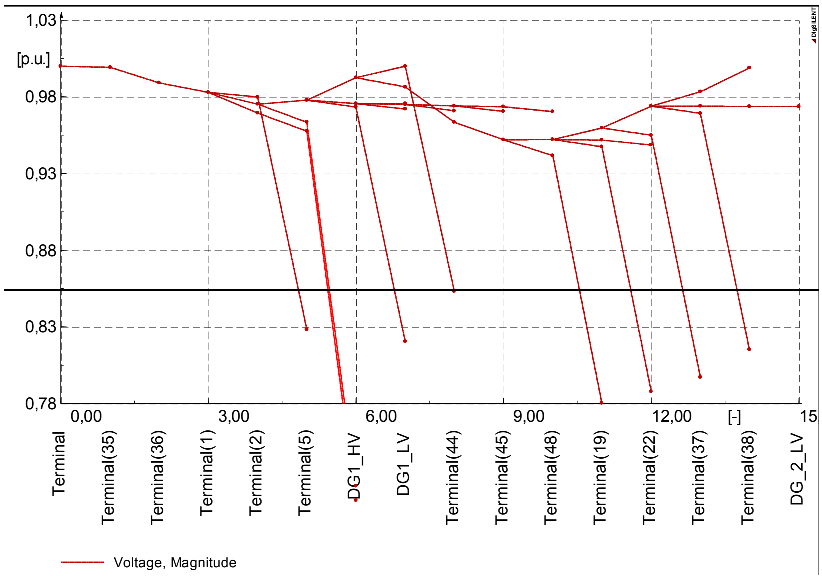

Figure 10: *Voltage values on terminals with 1150kW DG on Terminal 8*

DIgSILENT PowerFactory calculated the total active power losses of 273kW, which is remarkably close to the results for the same scenario estimated by ANN. Since the improvement of voltage value and the active power losses control is achieved, the proposed method of combining GA and ANN could provide a real-time solution for the economical operation of distribution systems.

7 CONCLUSIONS

Distributed Generation (DG) is increasingly common in electrical distribution networks, so its influence needs to be properly evaluated and rated in order to achieve the greatest benefit for DG itself as well as for the power system. A new optimization method based on Artificial Neural Networks (ANN) and Genetic Algorithms (GA) is proposed in this paper, and how the method could be used for the determination of size and location of DG is successfully demonstrated. This method is based on formulation by objective function and technical constraints. The rapidly obtained and correct solution for solving the given formulation is provided by using ANN, since they have the ability to solve non-linear mathematical problems extremely quickly and precisely. Back-propagation ANN is designed and trained via power-flow calculation results provided via DIgSILENT PowerFactory software for estimating the active power losses in the distribution system. In addition, 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 from each other by the power of DG, and individuals differ from each other by the terminal to which they are connected.

Improvements in voltage profiles and active power losses reduction made by the proposed method confirm the usefulness of the combination of ANN and GA for radial and networked distribution systems.

References

[1] **S. Biswas, S.K. Goswami, A. Chatterjee**: *Optimum distributed generation placement with voltage sag effect minimization*, Energy Conversion and Management, Elsevier, 2012.

[2] **K.S. Swarup, P.S. Subash**: *Neural network approach to voltage and reactive power control in power systems*, Intelligent Sensing and Information Processing, International conference, 2005,

[3] **S. Sumathi, P. Surekha**: *Computational Intelligence Paradigm – Theory and applications using Matlab®*, CRC Press, Taylor & Francis Group, 2010.

[4] **A.A. Abour El-Ela, Sm. M. Allam, M.M. Shatla**: *Maximal optimal benefits of distributed generation using genetic algorithms*, Electric Power System Research, vol.80, 2010., pp.869–877

[5] **E. Rezenia, S.M. Shahidehpur**: *Real Power loss minimization using interior point method*, Electric Power and Energy Systems, vol.23, 2001, pp. 45–46

[6] **K. Byeong-Gi , R. Dae-Seok**: *Optimal Voltage Regulation Method for Distribution Systems with Distributed Generation Systems Using the Artificial Neural Networks*, JEET, vol. 8, No 742, 2013.

[7] **H. Gavin**: *The Levenberg-Marquardt method for nonlinear least squares curve fitting problem*, Duke University, 2011.

[8] *DIgSILENT PowerFactory User's Manual*, Vol. I & 2, Edition 1, DIgSILENT GmbH, 2011.

[9] **D. Lukman, T.R. Blackburn**: *Modified Algorithm Of Load Flow Simulation For Loss Minimization In Power Systems*, IEEE/PES, Sydney, 2003.

[10] **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. 2007. pp. 954–959

[11] **J.M. Abdallah, A.R. Al-Zyoud**: *Voltage and Reactive Power Control Simulations Using Neural Networks*, IJSSST, vol.10, No.4, pp. 64–72

[12] **M. Vardarajan, K.S. Swarup**: *Differential evolutionary algorithm for optimal reactive power dispatch*, Electric Power and Energy Systems, vol. 30, 2008, pp. 435–441

[13] **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 3, 2011

[14] **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, 2012., pp. 133–136.

----

[15] **S. M. Hakimi, S. M. Moghaddas-Tafreshi, H. HassanzadehFard**: *Optimal sizing of reliable hybrid renewable energy system considered various load type*, J. Renewable Sustainable Energy 3, 2011

[16] **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, Volume 79, Issue 4, p.680–686, 2009.

[17] **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 18, pp. 626–645.

[18] **R.K. Singh, S.K. Goswami**: *Optimum allocation of distributed generations based on nodal pricing for profit, loss reduction, and voltage improvement including voltage rise issue,* Electric Power and Energy Systems, vol. 32, 2010., pp.637–644

[19] **N-C. Yang, T-H. Chen**: *Evaluation of maximum allowable capacity of distributed generations connected to a distribution grid by dual genetic algorithm*, Energy and Buildings, vol. 43, 2011., pp. 3044–3052.

[20] **M.R. AlRashidi, M.F.AlHajri**: *Optimal planning of multiple distributed generation sources in distribution networks: A new approach*, Energy Conversion and Management, vol.52, 2011., pp. 3301–3308.