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Analysis of power flow in electrical power systems with distributed generation using computational methods

Andressa Pereira Oliveira*, Laice Neves de Oliveira**
*(Federal University of Bahia's West, Doctor Manoel Novaes Avenue, 1064,47600-000, Bahia, Brazil
** (Department of Electrical Engineering - Faculty of Technology, University of Brasilia, Brazil

ABSTRACT
Due to the increase in electricity consumption in recent years and the diversification of the energy matrix with the presence of Distributed Generation, the electric power systems are getting bigger and more complex. Thus, it is becoming increasingly common to use power flow calculation to improve transmission line quality and performance. The classic and iterative Newton-Raphson method is widely used to solve the power flow problem, where the system solution is obtained from the steady state of the network, however for systems that fall into the poorly conditioned category. It can present high computational cost and possible instability in the Jacobian matrix inversions within the iterative process, due to the dimensions of the systems. Therefore, this paper presents a comparative analysis between the classic Newton Raphson method and the methods of computational intelligence, Artificial Neural Networks and Genetic Algorithms, using the MATLAB® software, in order to evaluate their convergence velocity, voltage profile impacts and losses. For IEEE-6, modified IEEE-6, IEEE-30, modified IEEE-30, IEEE-57, and modified IEEE-57 systems, system changes are due to integration with distributed generation.
Keywords - Artificial Neural Networks, Distributed Generation, Genetic Algorithms, Newton-Raphson, Power Flow.

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I. INTRODUCTION

The Distributed Generation (DG) that, according to INEE [1], refers to the production of energy close to consumption, has reached significant prominence in the energy market in recent years, bringing several benefits, such as the reduction of the main environmental impacts caused by the lines transmission, reduction in greenhouse gas emissions, diversification of the energy matrix, reduction of losses, in addition to allowing greater reliability in the energy system when they have an appropriate configuration.

Despite the advantages presented, the integration of distributed generation with the power system can also mean an increase in complexity to solve the Power Flow (PF) problem and attest to the need for more efficient computational methods in aspects such as convergence time and lower losses [2].

To solve the Power Flow problem, for many decades, only traditional iterative methods have been widely used, including the Newton-Raphson (NR) method and its decoupled versions [3]. These techniques seem to work well for operational points close to the nominal system conditions. However, the numerical performance of these methods varies inversely with the dimensions of the systems, that for the analysis of PF from systems with large dimensions, the method can present a high operational cost as well as find convergence difficulties, due to the sparse Jacobian matrix [4,5].

In order to optimize aspects such as convergence time and lower losses, which are fundamental during the planning process of the Electric Power System, over the years, new computational methods for solving the power flow have been proposed, among which stand out the use Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs).

In this context, Oliveira et. al. in [6] proposed the use of Artificial Neural Networks to solve the Power Flow problem for IEEE 6 and IEEE 30 bus systems integrated with Distributed Generators, using multilayered architectures with Backpropagation and Extreme Learning Machine training. The application of the computational intelligence technique proved, based on the results of the systems, that the method could solve the problem, as well as minimize the losses of the systems. Alves in [7] also carried out an assessment of the impacts of Distributed Generation on voltage stability, depending on the location and generation capacity, in which it was possible to highlight the relationship between the improvement in the voltage stability margin and the benefit in reducing losses caused by DG. Zarkovic in [8] presented an analysis in relation to active power losses, voltage drops and total harmonic distortion using Artificial Neural Networks for an IEEE 33 bus system with and without the presence of distributed generators. The results of the simulation also demonstrated a very good performance of the ANN to solve the problem of power flow. Tiwari et al. in [9] presented an analysis of voltage levels for the same system, comparing different training algorithms, using MATLAB® programming software. The best results were obtained with the Levenberg-Marquardt training methods and the Gradient Descent Backpropagation. Sousa in [10] proposed a PF analysis methodology for an IEEE-33 and IEEE-69 bus system using Genetic Algorithms to estimate the maximum power injected by Distributed Generators, without compromising the voltage quality in the analyzed systems, that presented satisfactory results and the algorithm demonstrated to meet the objective of the research.

Therefore, this article analyzes the impact of distributed generation on the electrical power system by comparing the classic Newton-Raphson method with computational intelligence methods Artificial Neural Networks and Genetic Algorithms, which were used to analyze the solution of the power flow in the IEEE-6, IEEE-30, IEEE-57 systems and their respective modifications for each of the systems, using the insertion of the distributed generation in load buses. The paper is divided into theoretical basis, in topics 1 to 3; the methodology, in topic 4, with the application of computational methods to solve the power flow; results and discussions, in topic 5, and conclusion.

II. POWER FLOW

The calculation of the Power Flow in a power system essentially consists of determining the state of the network, the distribution of flows and some other quantities of interest (voltage levels in the bars, active and reactive powers) [11]. This type of study is necessary to plan and design future expansions of power systems, as well as to determine the operational conditions of existing systems.

The basic equations of PF are obtained by imposing the conservation of the active and reactive powers in each node of the network, that is, the injected net power must be equal to the sum of the powers that flow through the internal components that have this node as one of their terminals. Where, four variables are associated with each system bus, in which two variables are known and two are calculated: P, net generation of active energy; Q, reactive power network; V, the magnitude of the voltage and θ, the voltage and the bus angle.

Each bus in the system corresponds to two non-linear equations expressed by (1) and (2), where Pi corresponds to the active Power in bar i; Qi, reactive power at bus i; Vi, Voltage modulus at bus i; Vj, Voltage module at bus j; θij - Phase angle difference between bar i and bar j; Gij - Line conductance between bus i and bus j of the nodal admittance matrix and Bij, Line conductance between bus i and bus j of the nodal admittance matrix.

III. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network is a technique inspired by human brain function and is composed of basic processing units: artificial neurons. The artificial neural network applied to the power flow can be considered as a computational mathematical model. Once trained, the ANN quickly returns the solution, producing an output through direct arithmetic operations [12].

3.1 BACK PROPAGATION

Multilayer perceptrons (MLP) have been successfully applied to solve many difficult problems, through their form of supervised training with a very popular algorithm known as backpropagation, which is a specific technique that back propagates the error from the output layer to the layer of entry, allowing the update of synaptic weights between the intermediate layers [13].

$$P_i = V_i^2 G_{ii} + \sum_{j=1;j\neq i}^{N} V_i V_j [B_{ij} sen(\theta_i - \theta_j) + G_{ij} \cos(\theta_i - \theta_j)] \quad (1)$$

$$Q_i = -V_i^2 B_{ii} + \sum_{j=1;j\neq i}^{N} V_i V_j [G_{ij} sen(\theta_i - \theta_j) + B_{ij} \cos(\theta_i - \theta_j)] \quad (2)$$

According to Silva et al. in [14], the algorithm consists of two phases: forward and backward. The first phase to be applied is “forward propagation”, in which a pattern is presented to the network's input layer and is propagated between the layers, until the response is produced by the output layer. In the second phase, backward, the output obtained is compared to the desired output for this standard and then the error is calculated. If it exists, the error is propagated from the output layer to the input layer and the synaptic weights are modified, in order to reduce its errors with each iteration.

IV. GENETIC ALGORITHMS

Genetic Algorithms are search and optimization methods inspired by the mechanisms of evolution of populations of living beings [15]. Flexibility has made Genetic Algorithms one of the most widespread techniques of Evolutionary

Computing, in addition to the relative simplicity of implementation and effectiveness in carrying out global search in different environments.

The method of executing an GA consists of applying the principles of survival of the fittest individual, reproduction and mutation in a population with possible solutions to a problem, so that, during the iterations, successively, better results are obtained and closer to the optimal solution successively [16]; each iteration represents a generation of the population.

V. METHODOLOGY

The types of voltage magnitude control, generally represented in power flow programs, are control by reactive injection and tap adjustment (phase transformers) [11]. In this work, however, control is performed by active power injection, using Distributed Generators in IEEE-6, IEEE-30 and IEEE-57 bus systems, comparing the results obtained with MATPOWER©. The IEEE 6 bus system, in Fig. 1, has its transmission line parameters presented in [17]. Bus 1 corresponds to the slack bus; bus 2 is generation bus (PV) and buses 3, 5 and 6 are load buses (PQ). The capacitor banks are connected to buses 4 and 6. The transformers are connected between buses 3-4 and 5-6. The IEEE-30 system consists of 1 slack bus, 5 buses of fixed active power generation, 24 load buses, 37 transmission lines, 4 transformers with variable taps. The transmission line parameters are shown in [18]. The IEEE-57 bus system has 1 slack bus, 6 PV buses and 50 PQ buses. The system parameters are shown in [19].

5.1 ARTIFICIAL NEURAL NETWORKS APPLIED TO THE SOLUTION OF THE POWER FLOW PROBLEM

The Neural Network model used to solve the Power Flow problem was the MLP, since the ANN-MLP are capable of solving complex problems with a degree of relative difficulty similar or superior to the problem of non-linearity of the PF [5]. In this work, the ANN was trained using the Levenberg– Marquardt Backpropagation algorithm. The code was implemented using the functions of the MATLAB® software, in order to define the tolerance for the error, allowing the scanning between the minimum and maximum values for the DGs with a difference calculated equally between the values and same number of elements for all variables.

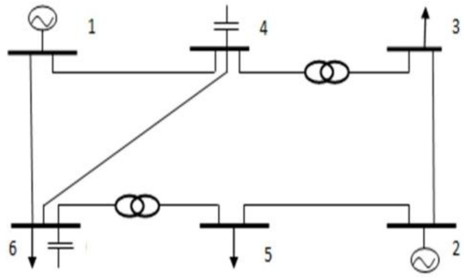

Fig. 1 IEEE 6-bus system, [17].

The training scenarios were criated by inserting Distributed Generators in different load buses for the IEEE-6, IEEE-30 and IEEE-57 systems, with minimal variations between the lower and upper limits of active power, as shown in Table 1. The selection criteria defined for the initial allocation of generators were for the load buses, with the lowest voltage levels and with the highest demands.

The input variables for ANN training are the active and reactive powers corresponding to each bus in the system. Meanwhile, the desired output variables (Target) are the voltage magnitudes and the angle of the power flow solution with DG, using the classic Newton-Raphson method.

The architecture used was defined with an input layer with two variables, a hidden layer with the logistic-sigmoid function (logsig) of activation and an output layer with the linear function. The number of neurons in the hidden layer was obtained through tests and comparisons of the errors of the evidence data during the continuous training process, where the composition of the neurons of the hidden layer was varied dynamically and the networks that presented the lowest mean squared error were stored. The number of neurons in the hidden layer for each ANN as a function of the system is shown in Table 2.

Table 1. Active power injection data for IEEE 6, 30 and 57 bus systems.

Parameter	IEEE-6	IEEE-30	IEEE-57
DGs allocated	2	3	5
Lower Limit (MW)	0	0	5
Upper limit (MW)	5	5	10
Scenarios used (amount)	626	9261	10563

5.2 GENETIC ALGORITHMS APPLIED TO THE SOLUTION OF THE POWER FLOW PROBLEM

For the allocation of new DGs in the IEEE-6, IEEE-30 and IEEE-57 systems, the genetic algorithm must evaluate the indicated locations and determine the capacity of each DG, such that the overall benefit for the systems is maximized. In this paper, Binary Genetic Algorithms were used, in which the points in the solution space are encoded as a 0 or 1 bit string within each individual.

Table 2. Dimensions of neuron layers.

System	Neurons of hidden layer
IEEE-6	6
IEEE-30	15
IEEE-57	25

The maximum number of generations was defined as the stopping criterion, this value being defined by trial and error. From the results obtained it was noticed that there would be no significant advantages in "evolving" populations for more than 100 generations for the IEEE-6, IEEE-30 and IEEE-57 systems, considering active losses as a parameter. The other parameters used in the configuration of the Genetic Algorithms are shown in Table 3.

The individual is usually the most important component of the Genetic Algorithm, as it contains information about the parameters that must be optimized and, at the end of the process, indicates the best result obtained. For this work, individuals represent the values of active powers injected in up to n distributed generation connection buses, where n = 2 for the IEEE-6 bus system, n = 3 for the IEEE-30 bus system and n = 5 for the IEEE-57 bus system. The positioning of the DGs is initially carried out at random, respecting the restrictions so that there is no allocation in repeated buses and generation buses. Individuals are generated within a search space delimited by the DG's generation capacity, which ranges from 0 to 5 MW for systems with 6 and 30 buses, and from 5 to 10 MW for the system with 57 buses.

Table 3. GA parameters for IEEE 6, 30 and 57 bus systems.

Parameter	IEEE-6	IEEE-30	IEEE-57
Population Size	35	100	150
Crossover Rate	0,80	0,80	0,80
Mutation Rate	0,01	0,01	0,01
Max. iterations	100	100	100

For a given individual, from the values obtained from voltage magnitude and phase angles, the total losses are given by (3), where: Nbr corresponds to the number of transmission stretches; gb, conductance of the transmission section; Vtb and Vfb, voltage modules (p.u.) on the terminal buses of section b; θfb and θtb, phase angles (radians) in the terminal buses of section b.

Each individual will be evaluated according to the calculation presented by equation in (4), where Fit (i) represents the fitness of the i-th individual during the evolutionary process and Pt (i) the value of losses associated with configuration i. Since it is a minimization problem, fitness is inversely proportional to the system losses calculated in (3).

VI. RESULTS AND DISCUSSIONS

The algorithms were implemented in the

$$P_t = \sum_{b=1}^{Nbr} g_b [V_{fb}{}^2 + V_{tb}{}^2 - 2V_{fb}V_{tb}\cos(\theta_{fb} - \theta_{tb})] \quad (3)$$

MATLAB® software. The simulations were performed on a computer with the configurations of the Intel® Core ™ i3-3110M processor, 2.4 GHz; installed memory (RAM) of 4 GB; and 64-bit operating system.

6.1 IEEE 6-BUS SYSTEM

The ANN training data was combined in 626

$$F_{it}(i) = \frac{1}{100 * P_t(i)} \quad (4)$$

scenarios. The values of active losses were analyzed considering 1 DG fixed in bus 4, varying the values from 0 to 5 MW and another DG fixed in bus 6. Fig. 2 shows a comparison between the NR, ANN and GA methods for the lowest losses obtained and the respective location of the DG.

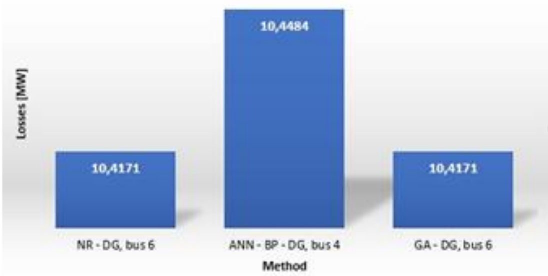

Fig. 2 Comparison between the methods applied to the IEEE-6 bus system.

The active losses presented by the NR method without the presence of DG is 13.7056 MW. Therefore, there is a significant reduction in losses with the insertion of distributed generators.

Fig. 3 presents the mean square error curve for the best model of the IEEE-6 bus system, where it is possible to observe the validation in 229 periods, with an error of less than 10-15.

Fig. 4 shows the active losses as a function of the number of generations obtained from the search carried out by the Genetic Algorithm for allocation of 1 DG. The value of active power for the Distributed Generation that generated the lowest loss (10.4171 MW) was 5 MW. Note that from generation 50, the lowest value is obtained and stabilized by the next generations. The computational cost presented by the genetic algorithm was 19 s, while the NR obtained the same loss value in 0.003990 s. The ANNs obtained, on average, a training time of 3 min for each scenario. However, after being trained, the result was obtained around 1s.

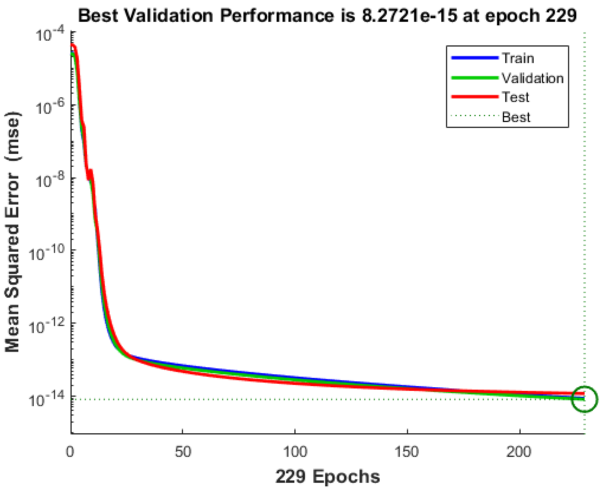

Fig. 3 Mean Square Error for the best model of the IEEE-6 bus system.

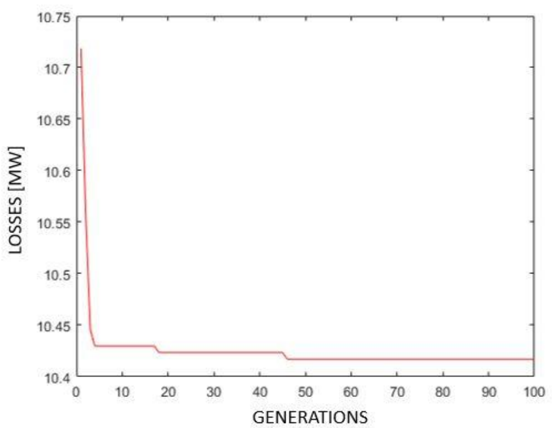

Fig. 4 Losses per generation for the IEEE-6 bus system.

6.2 IEEE 30-BUS SYSTEM

In the IEEE-30 system, training for ANN was carried out considering the insertion of 2 and 3 DGs ranging from 0 to 5 MW, totaling 9261 scenarios. According to Fig. 5, the best model for the solution of PF in IEEE-30 was obtained by inserting DG in buses 17 and 27 simultaneously. The results were obtained with the insertion of 2.5 MW in each DG in the bus, which resulted in a reduction of about

6.4 MW in the system, since the value of losses without DG for IEEE-30 is 17.5570 MW.

Scenarios were generated using the simultaneous variation of the active power of 3 distributed generators, however, as the loss reduction was not significant compared to the use of 2 DGs, as can be seen in Fig. 5, we opted to perform analysis of losses between the methods used considering the insertion of 2 DGs.

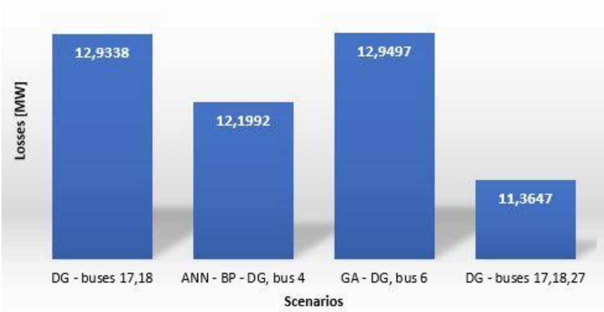

Fig. 5 Best scenarios for ANN with the insertion of Distributed Generators.

Fig. 6 and Fig. 7 show the graphical behavior of magnitude and voltage angle for all buses in the IEEE-30 system, where the responses corresponding to the best scenarios of the NR, ANN methods appear parallel to each other, proving the training efficiency carried out at ANN. Note that in all buses the magnitudes of the voltages are within the minimum and maximum limits adopted, 0.9 p.u. and 1.1 p.u., respectively.

Table 4 shows a comparison between the value of active and reactive losses and the computational cost that was required for each method. Although the GA presents lower losses, which were obtained with the allocation of DGs in buses 12 and 10, with the levels of active power of 3.8824 MW and 3.8627 MW, respectively, the computational cost presented was higher than the other methods for the analyzed 30-bus system.

6.3 IEEE 57-BUS SYSTEM

Figure 8 shows the voltage magnitudes of the analyzed system without the insertion of distributed generators, where the buses, 18, 19, 25, 26 and 31 show a voltage drop. As a result, 5 DGs were allocated to each of these buses, with the active power ranging from 5 to 10 MW.

Figure 9 presents a comparison between the NR, ANN and GA methods for the best scenarios obtained and the location of the distributed generators, where there is a significant reduction in losses that reached 47.7%, when compared to active losses without the DG insertion which is 48.4517 MW.

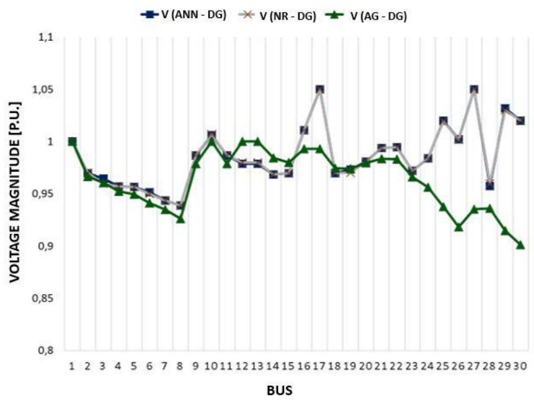

Fig. 6 Comparison between Voltage Magnitudes for the methods applied to the IEEE-30 bus system.

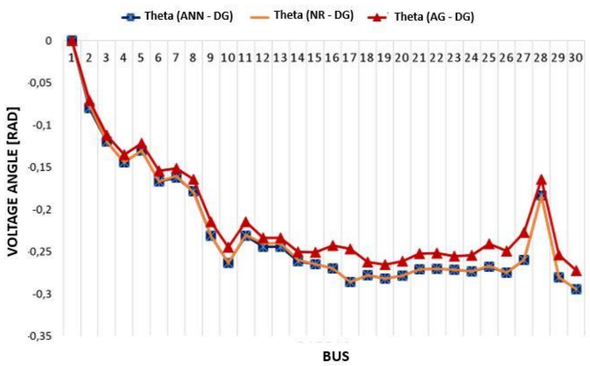

Fig. 7 Comparison between voltage angles for the methods applied to the IEEE-30 bus system.

Table 4. Comparison between the methods applied to the IEEE-30 bus system.

Scenario	Losses [MW]	Losses [MVAR]	Computacional Cost [s]
ANN – DG, B* 17, 27	12,1992	50,5030	0,2388
NR – DG, B* 17, 27	12,2001	50,5055	0,4443
GA – DG, B* 12,10	12,2043	41,0754	523,51

B* - short for Buses.

For the NR and ANN methods, the insertion of 7.5 MW into each specified bus was considered, while the values of active power used by the GA were in DG-24 of 6.1176 MW, in DG-25 of 5.5686 MW, in DG-28 of 5.8824 MW, in DG-29 of 6.5882 and in DG-42 of 7.2157 MW. Thus, the best scenario obtained by GA for the IEEE-57 system presented active losses and reactive losses of 25.3610 MW and 115.6038 MVAr, respectively.

Fig. 10 shows the linear regression for the best scenario obtained with ANN, for the mean quadratic error with the validation in 207 epochs and error of the order of 10^{-14}. The voltage magnitudes after the insertion of distributed generators are shown in Fig. 11, in which the stabilization of the voltage levels for each bus can be observed within the voltage limits adopted in all methods.

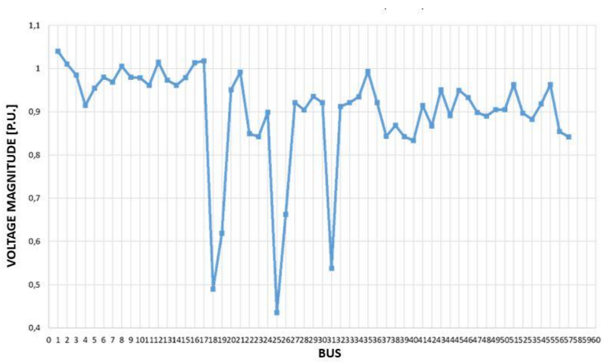

Fig. 8 Voltage Magnitudes for the IEEE-57 system without DG insertion.

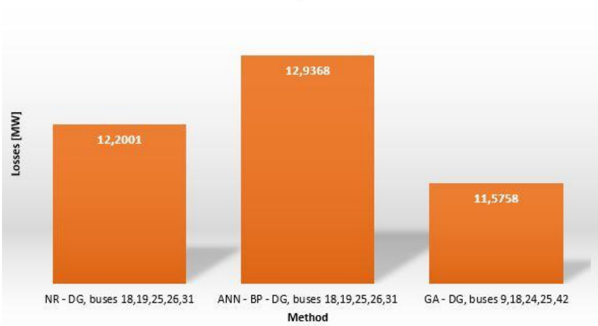

Fig. 9 Comparison of Active Losses between the methods applied to the IEEE-57 bus system.

VII. CONCLUSIONS

The results showed that the use of the solution method involving Genetic Algorithms obtained less losses in the allocation of distributed generators for all the systems analyzed, however, GA is the method that has the highest computational cost in comparison with the iterative method of classic NR and ANN trained with the Backpropagation algorithm, as it is a search and optimization method.

The ANNs presented values of magnitude of voltage and losses close to that presented by the NR, which is the most widely used method for solving the power flow, proving the efficiency of the training performed, in addition to the low computational cost, since once trained, the response returned by ANN is instant. Another advantage presented in its use is that, in practice, if the electrical system receives new equipment or a new generation, due to the ability to generalize the acquired knowledge, it is not necessary to carry out new training, making the process dynamic.

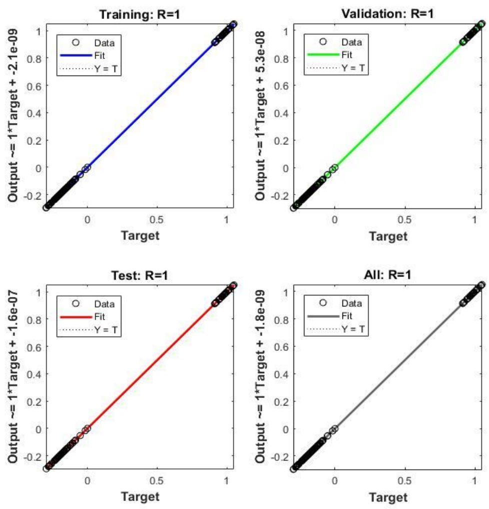

Fig. 10 Linear Regression for the best model of the IEEE-57 bus system.

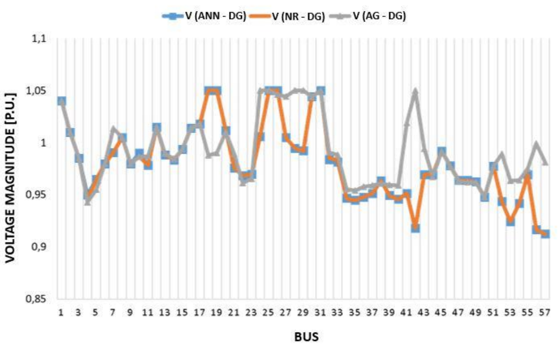

Fig. 11 Voltage magnitudes for the IEEE-57 system with insertion of DGs.

It is considered perceptible the reduction of losses in the systems due to the presence of distributed generation, the improvement in voltage profiles and possible load reductions in the network, thus allowing energy utilities to postpone certain reinforcement investments. Thus, for the planning of Electric Power Systems based on the solution of the PF problem, the ANN architecture with training, using the Backpropagation algorithm, will produce responses with low computational cost and with efficiency similar to the classic NR method.

GA was able to provide the best power values for minimizing system losses, despite having a high computational cost, which is considered an important variable by the electrical system planning sector, especially with regard to restoration time, if the solution of the problem is necessary after a contingency situation.

REFERENCES

[1]. INEE, Instituto Nacional de Eficiência Energética: O que é Geração Distribuída, 2008.

[2]. F. C. Lucchese, F. Anselmini, C. C. Martins, M. Sperandio, Análise do impacto da geração distribuída fotovoltaica na rede elétrica da Universidade Federal de Santa Maria, *VII Congresso Brasileiro de Energia Solar*, Gramado, 2018.

[3]. W. D. Stevenson, *Elementos de análise de sistemas de potência*. (McGraw-Hill do Brasil, 1994).

[4]. Y. Feng, *Solving for the Low-Voltage/Large-Angle Power-Flow Solutions by using the Holomorphic Embedding Method*, Doctoral Dissertation, Arizona State University, 2015.

[5]. H. H. Muller et al, *Redes neurais artificiais aplicadas a sistemas de potência*. Faculdade de Engenharia Elétrica e de Computação da UNICAMP, São Paulo, 2008.

[6]. A. P. Oliveira, K. N. Souza, L. N. Oliveira, S. F. Meneses, Analysis of Artificial Neural Network Methods in the Power Flow Problem with Distributed Generation, *In Congresso Ibero Americano em Métodos Computacionais em Engenharia*, Natal, RN, 2019.

[7]. A. A. Alves, *Avaliação da estabilidade de tensão nos sistemas de distribuição considerando a injeção de potência da geração distribuída*. Dissertação de Mestrado, Universidade Estadual do Oeste do Paraná, 2016.

[8]. M. Zarkovic, D. Sosic, ANN for Solving the Harmonic Load Flow in Electric Power Systems with DG, *Mediterranean Conference on PowerGeneration Transmission Distribution and Energy Conversion (MedPower 2016)*, pp. 1-4, 6-9 November, 2016.

[9]. S. Tiwari, M. A. Ansari, K. Kumar, S. Chaturvedi, M. Singh, S. Kumar, Load Flow Analysis of IEEE 14 Bus System Using ANN Technique. *In 2018 International Conference on Sustainable Energy, Electronics, and Computing Systems (SEEMS)*, pp. 1-5, IEEE, 2018.

[10]. A. L. Sousa, *Estimativa da capacidade de Hospedagem de Geração Distribuída em Redes de Distribuição via Algoritmos Genéticos*, Dissertação de Mestrado, Universidade Federal do Pará, 2019.

[11]. A. J. Monticelli, *Fluxo de carga em redes de energia elétrica* (E. Blucher, 1983).

[12]. E. Masson, Y. J. Wang, Introduction to computation and learning in artificial neural networks, *European Journal of Operational Research*, 47(1), 1-28, 1990.

[13]. P. D. P. Salazar, *Monitoramento em tempo real da estabilidade de tensão usando redes neurais artificiais*, doctoral dissertation, University of São Paulo, 2018.

[14]. I. D. Silva, D. H. Spatti, R. A. Flauzino, *Redes neurais artificiais para engenharia e ciências aplicadas* (São Paulo: Artliber, 2010) 23(5), 33-111.

[15]. R. L. Haupt, S. Ellen Haupt, *Practical genetic algorithms* (Wiley-Blackwell, 2004).

[16]. P. Fleming, A. Chipperfield, Genetic algorithms in engineering systems. *IEE Control Engineering Series* 55, 1997.

[17]. A. Q. Badar, B. S. Umre, A. S. Junghare, Reactive power control using dynamic particle swarm optimization for real power loss minimization. *International Journal of Electrical Power & Energy Systems*, 41(1), 133-136, 2012.

[18]. Assembla, IEEE 30-Bus Test System, 1961. Disponível em: <https://subversion.assembla.com/svn/load-flow-analysis/Documentation/IEEE%2030%20bus%20test%20case/ieee30bus.m>. Acesso em: 17 jan. 2020.

[19]. MATPOWER, IEEE 57-Bus Test System, 1993. Disponível em:<https://matpower.org/docs/ref/matpower5.0/case57.html>. Acesso em: 17 jan. 2020.

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