# ANALYSIS OF ARTIFICIAL NEURAL NETWORK METHODS WITH APPLICATION IN REACTIVE POWER FLOW CONTROL

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***Abstract.*** *In the power system is necessary that the voltage is stabilized within the presented limits for energy quality be provided. The traditional method that solves the problem of Power Flow is the Newton-Raphson. In this work, which is developed in MATLAB® software, the method of artificial neural network is used to solve the problem with the goal of reducing the losses of the IEEE Systems 6 and 30 bus. The architectures used are the multilayers perceptrons with the backpropagation and Radial Basis Function training. The Hopfield, that does not work independently, is added to backpropagation and Radial Basis Function to form two other architectures. The results are analyzed and compared with outputs of PSO (Particle Swarm Optimization), MatPower and PowerWorld©, to select the lower losses and better scenarios.*

***Keywords:*** *Artificial Neural Network, Power Flow, Losses.*

# 1 Introduction

The Electrical Power System (EPS) is a set of devices operating together in a coordinated manner in order to generate, transmit and supply electricity with quality and reliability to consumers (Castro, 2014). For the perfect functioning of the system, there are some essential conditions related to the power quality: frequency and magnitude of the voltage to be constant as well, the system must have reliability, availability and safety (Cunha, 2014).

The system state violated with stress levels can be improved through the adjustments of existing tensions control devices and also the optimal planning of reactive sources considering the physical, economic and operation (Quizhi, 2011). Numeric technics based on heuristic search and evolutionary algorithms have been aplied in the resolution and optimization of electrical systems. (Bhattacharyya and Goswami, 2007) implemented the heuristic and evolutionary approach to finding the reactive power problem solution for controlling generation of reactive generators and position of tap transformers of an interconnected power system. (Badar et al., 2012) and (Leeton et al., 2010) described the Particle Swarm Optimization (PSO) with dynamic weights applied to reduce losses in the system. The voltage generation bus, the tap position of the transformer and the switchs of shunt capacitors are used as variables by control of the reactive power flow. (Mamandur and Chenoweth, 1981) applied to different percentages of load optimization for safe voltage and reactive power. (Vaisakh and Rao, 2005) used the differential evolution to find the optimal solution. (Rahideh et al., 2006) presented a method based on fuzzy logic for voltage control or reactive power and simultaneously reduce losses in the power system. In this proposal, the level of violation of the voltage bus and also control ability of devices such as capacitors or shunt reactors and variation of tap transformers have been translated into fuzzy logic.

The Artificial Neural Network (ANN) is considered a technic of artificial intelligence, which has been applied in many areas of electrical power systems. The ANN can become a support tool to the conventional method of Newton-Raphson to be faster and involve the advanced Power Flow (PF) problem applications, due to the complexity of electrical systems nowadays. Thus, the aim of this study is to define the most efficient architecture applied to circuits with few sources of reactive and PV buses, such as IEEE-6 system until spotted systems, and many sources of reactive and PV buses, as in IEEE-30 system. Some Neural Network (NN) applications used in this work are proposed in the literature to solve the power flow problem as the backpropagation in (Paucar and Rider, 2002), Hopfield model (Hartati and El-Hawary, 2009) and Radial Basis Function (Karami and Mohammadi, 2008). The results of the NN were analyzed and compared with outputs of PSO (Prasanthi, P. S.; Hazeena, K. A., 2013), MatPower and PowerWorld©.

The present paper is divided into the theory necessary to the comprehension of this subject in the topics 2 and 3 (Power Flow and Artificial Neural Network); the methodology in topic 4 of the ANN in reactive power flow; results and discussion in topic 5 and conclusion.

# 2 Power Flow

The PF analysis is an indispensable part of the steady-state study of the transmission and distribution of electrical power system. In attendance of loads presupposes the availability of adequate and reliable tools, especially when the system involved is large. The steady-state power system can be determined by solving the equations of power flow, which are represented by non-linear algebraic equations. This problem is also known as load flow. The main goal is to calculate the magnitude of voltage and angles of all buses and after, the PF's of the transmission lines (Nascimento, 2013). Thus, it is also possible to determine the level of losses, as well as to optimize them for efficient network operation.

The starting point for the study of any power flow is to prepare the data generation and load to the power grid that is described by the admittance matrix Y of Equation (1) according to (Machowski et al., 2008). Where, $I_i$ is the current at node i, $V_i$ is the voltage at i and $Y_{ij}$ bus is the admittance in ij branch.

$$\begin{bmatrix} I_1 \\ \vdots \\ I_i \\ \vdots \\ I_N \end{bmatrix} = \begin{bmatrix} Y_{11} & \dots & Y_{1i} \dots & Y_{1N} \\ \vdots & \ddots & \vdots \ \ddots & \vdots \\ Y_{i1} & \dots & Y_{ii} \dots & Y_{iN} \\ \vdots & \ddots & \vdots \ \ddots & \vdots \\ Y_{N1} & \dots & Y_{Ni} \dots & Y_{NN} \end{bmatrix} \begin{bmatrix} V_1 \\ \vdots \\ V_i \\ \vdots \\ V_N \end{bmatrix} \tag{1}$$

The basic load flow equations are obtained imposing the conservation of active and reactive power at each node of the network, i.e., the injected net power must be equal to the sum of the powers that flow through internal components that have this node as a of its terminals. These analysis is according to the First Law of Kirchhoff. The Second Kirchhoff's Law is used to express the power flows to the internal components as functions of the voltages (states) of its terminal nodes (Machowski et al., 2008). Four variables are associated with each system bus: P, net generation of active power; Q, reactive power net; V, the bus voltage magnitude and θ the bus angle. A common practice in PF study is to identify the three types of buses on the network that may include: load, when P and Q are known; generating, when P and V are known and also reference or slack bus or swing, where V and θ are known. In each bus, 2 of the 4 variables are known and 2 are calculated. Each system bus has two equations.

The relationship between the input data (injection of active and reactive power in the nodes) and the state variables (voltage magnitude and angle nodes) is non-linear, as shown in Equations (3) and (4), according with (Machowski et al., 2008) in polar coordinates. So that, $G_{ij}$ is the conductance and $B_{ij}$ is the susceptance in each branch according to Equation (2).

$$Y_{ij} = G_{ij} + jB_{ij} \tag{2}$$

$$P_i = V_i^2 G_{ii} + \sum_{j=1;j\neq i}^{N} V_i V_j [B_{ij} \operatorname{sen}(\theta_i - \theta_j) + G_{ij} \cos(\theta_i - \theta_j)] \tag{3}$$

$$Q_i = -V_i^2 B_{ii} + \sum_{j=1;j\neq i}^{N} V_i V_j [G_{ij} \operatorname{sen}(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)]. \tag{4}$$

## 3 Artificial Neural Network

Artificial Neural Network is a technic inspired by the function of human brain and it is composed of basic processing units: the artificial neurons. The ANN applied to the power flow can be considered as a conventional numerical method. Once trained, the ANN is able to quickly present the solution on fast time and it produces an output through direct arithmetic operations.

The purpose of training is to attribute the synaptic weights to appropriate values with the goal of producing the desired output set, or at least a consistent solution, with an error range defined. The learning process intention is to find a weight by applying a rule that defines this learning. In ANN, each process of training corresponds an epoch. (Másson and Wang, 1990).

The multilayer perceptrons have been successfully applied to solve many difficult problems, through its form of supervised training with a very popular algorithm known as error back propagation algorithm. The backpropagation is a technic which uses gradient descent to reduce the error. In this paper, the process uses the sigmoid function.

The Radial Basis Function (RBF) has emerged as a variation of Artificial Neural Networks in the late 80. The RBF networks are made up of three layers connected: the input layer; hidden layer (or RBF), using generally Sigmoidal basis functions; and output layer. The first layer uses neurons of radial basis functions, that uses the data input in clusters which has a plurality of nonlinear patterns, while the output is linear. Input nodes are connected to the neurons of the hidden layer and the output neuron to the $n^{th}$ neuron. The output layer classifies the received patterns of the previous layer, hidden layer, through the exit sum of weights in each unit.

The Hopfield network uses a linear programming technic efficient for classification into ANN. The outputs of the neurons are discretized (the MLP type) due to activation function be of step with saturation values and can only assume values -1 or +1, that is the violation of standards. (Haykin, 2001).

## 4 ANN Application in Reactive Power Flow

The control of the voltage magnitude by the reactive injection and the transformer tap adjustment are the types of control usually represented in power flow programs.

The application of ANN in this study consisted of training scenarios that presents combination of reactive sources, the losses is calculedin each scenario. The results obtained are compared with MatPower (Zimmerman and Murillo-Sánchez, 2010) and PSO (Prasanthi, P. S.; Hazeena, K. A., 2013) to the IEEE-6 (Badar et. al., 2012) and IEEE-30 (Assembla, 2013) systems. Also, with the PowerWorld© for IEEE-6 system.

The IEEE-6 system, in Figure 1, has its transmission line parameters as shown in (Badar et al., 2012). The bus 1 is the reference bus; PV is the bus 2 and the buses 3, 5 and 6 are load buses. The capacitor banks are connected to the buses 4 and 6. The transformers are connected between buses 3-4 and 5-6.

The IEEE-30 system, consisting of 30 buses and 41 branches, has diagram and transmission line parameters as (Assembla, 2013). The work was divided into the combination of three architectures for using in the power flow: Backpropagation, Hopfield and Radial Basis Function.

The admittance matrix of the system was built to constitute the input data of the ANN composed of the input data (P) and the desired output (T), known as Target. Through the power flow equation was defined Equations (5) and (6), that generate $G_d$ and $B_d$ to the input, as real numbers. The equations defined in (Paucar and Rider, 2002) was used to minimize the number of inputs in the ANN, but the goal in this paper is to use the diagonalization without loss of accuracy.

$$G_d = V_g^2 . G_d^\lambda - P_d + Pg_{pv} \tag{5}$$

$$B_d = -V_g^2 . B_d^\lambda - Q_d \tag{6}$$

Where, $G_d$ and $B_d$ are the conductance and susceptance, respectively, resulting from the Equations (5) and (6); $V_g$ is the generation of bus voltage, defined as 1 p.u.; $G_d^\lambda$ and $B_d^\lambda$ are the conductance and susceptance, respectively, extracted from the matrix after diagonalization by eigenvalues and eigenvectors; $P_d$ and $Q_d$ are the active and reactive power, respectively, the calculated bus; $Pg_{pv}$ is the active power of PV bus.

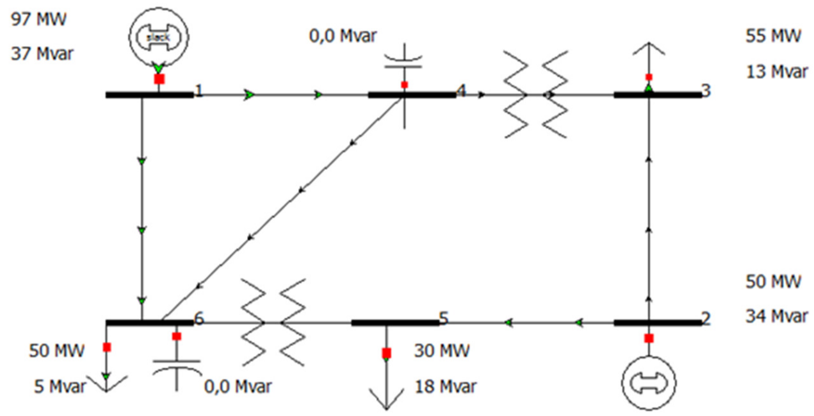


Figure 1. IEEE-6 system built in PowerWorld©.

The training of the ANN's were divided into scenarios. The scenarios were formed by simultaneous variation of taps and reactive, which is related to each bus. Each scenario was necessary to produce the values of the voltages and angles for each bus with greater accuracy and after, reducing system losses. The input variables for the ANN training are G and B, resulting from Equations (5) and (6); active powers of the reference bus, PV and load. The desired output variables are the voltage magnitudes and angles of the Newton-Raphson solution, without the control of taps and reactive; and variables of control for the system.

In the IEEE-6 system, the column of variables of control has two reactive and two tap variables, which results in the analysis of 625 scenarios as illustrated in Figure 2. In the IEEE-30 system has 18 variables of control, 8 taps and 10 reactives variables, which results in 69 billion scenarios. Because of the large number of scenarios, which were not all analyzed in this work, the choice of numbers which form the matrices of control came from the values randomized, in order to define the boundary of that set. The methods with ANN (RBF, Hopfield and Kohonen) were used to choose the data that corresponds the central point to select the control variables of the training: (a) the RBF architecture does not work for this situation, because it needs P and T input and in this case, it's looking for a classification method; (b) the Hopfield and Kohonen architectures have binary outputs, so they can not classify what are the data for the control.

From the data obtained, we selected those from the minimum and maximum limits of each variable. The data for each variable were put in the column array that is part of the ANN control matrix.

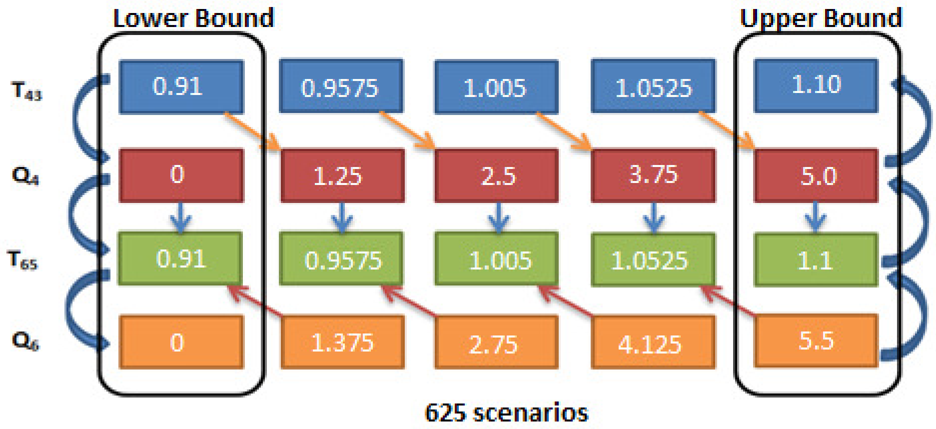


Figure 2 - Illustration for combinations of IEEE-6 scenarios.

## 5 Results and Discussion

The results produced were analyzed and compared with other approaches that solved the power flow problem through numerical methods. As an example, PSO (Particle Swarm Optimization) which is an unconventional method of search, based on the social behavior of the assembled birds or fish shoals. The PSO is applied in reactive power optimization, which implies the reduction of losses in a power electrical system (Badar et. al., 2012) and (Kumar and Chaturvedi, 2013).

The simulations were performed on notebook with the following settings: Intel® Core™ i5-2450M processor, 2.5 GHz; Installed memory (RAM) of 4 GB; and 64-bit operating system.

## 5.1 IEEE-6 system

The backpropagation for IEEE-6 system trained 125 scenarios with different levels of reactive, using the multilayer architecture and approximately 6 neurons at the hidden layer. The value of system losses and the amount of iterations were the main variables for analysis of results, the difference between methods for all scenarios was less than $10^{-3}$. In this case, it is observed in Table 1 values of the control taps of transformers that produced a loss of 5.23 MW. Therefore, the best scenario is resulting in lower losses in the system.

For the 125 scenarios that have been trained and 16 of them had best linear regressions. In the analysis of 16 scenarios, beyond of the less amount of iterations and reactive losses, the best linear regression was also analyzed for the choice of optimal scenario.

Table 1. Values for the optimal scenario according the backpropagation.

| Losses [MW] | Control 3 | Control 4 | Control 5 | Control 6 |
|---|---|---|---|---|
| 5.23 | 1.052 | 3.750 | 0.957 | 4.125 |

In the process of training individual scenarios, some relevant considerations were identified: (1) the better the convergence regression in the first iteration, a bigger loss was produced, above 15 MW; (2) the smaller numerical loss, which is not technically acceptable, has a better linear regression, but the curves of the Mean Square Error (MSE) are distant from each other; (3) the higher the individual distance between the training, testing and validation curves, bigger are the losses; (4) the more parallel the MSE curves are together, the better the linear regression curves and smaller are the losses; (5) when convergence occurs very fast, on the 1st iteration, for example: better linear regressions, but with the distant data of the regression lines; high losses (27 MW); and training curve initially closer; (6) difficult convergence scenario with the variables of control: $tap_{34} = 0.9575$; $Q_4 = 1.2500$; $tap_{56} = 0.9575$; $Q_6 = 4.1250$; (7) bigger distance between the MSE curves: bigger losses (over 15 MW) and great linear regressions, but with distant data curves; (8) with great linear regressions, i.e., close to 1, and data close to the regression curve, if the curve is far from ideal, Target (Y), losses are high; (9) great linear regressions, MSE curves with the default behavior and very low losses: high amount of iterations. So, if the curves are distant, the losses are high and the convergence is fast.

In the RBF training, the convergence time, the number of iterations and the difference between the methods in voltage angle characteristics were important in the process. The convergence time is instantaneous; convergence always happens in the first iteration independent of how many attempts the operator put the training to take place; and the difference in voltage angle between the methods is zero, confirming the theory to such an architecture (Haykin, 2001). Table 2 presents the scenario with the lowest losses calculated on the RBF. From the relation of losses and error, difference between the methods, voltage, as shown in Figure 3, it is possible to note that when the numerical value of the error grows, bigger are the losses.

Tabel 2. Values of great scenarios according to RBF.

| Losses [MW] | Control 3 | Control 4 | Control 5 | Control 6 |
|---|---|---|---|---|
| 9.91 | 1.0525 | 2.500 | 1.0525 | 4.1250 |
| 9.92 | 1.1000 | 3.750 | 1.0525 | 4.1250 |

Figure 4 shows the output voltage in the system bus of the best scenario from the 125 training for the backpropagation. Whereas in Figure 5 shows the output voltages for the best training scenario with RBF. Note that, in bus 3 of Figures 4 and 5, even for different scenarios, there is a dip voltage and this is a load bus. To the bus 5 of Figure 5, also a loading bus and dip voltage, the voltage magnitude is not in the minimum value of the transformer tap control connected to this bus, 0.91.

The Hopfield network produces binary outputs, and therefore should not be used directly to solve the power flow problem. In this paper, the analysis of Hopfield architecture was realized combined with the network backpropagation and the RBF. The results obtained by Hopfield architecture with backpropagation show that, mathematically, the method is feasible. For the scenario of Table 3, with tap and reactive values in the minimum, the system loss value of approximately 340 W is impractical. Because of this characteristic, the value of loss might occur only on an ideal system. While in Hopfield architecture with RBF, the scenarios presented, on average, losses of 19 kW, value considered low when compared to the values produced in this paper and in (Prasanthi and Hazeena, 2013).

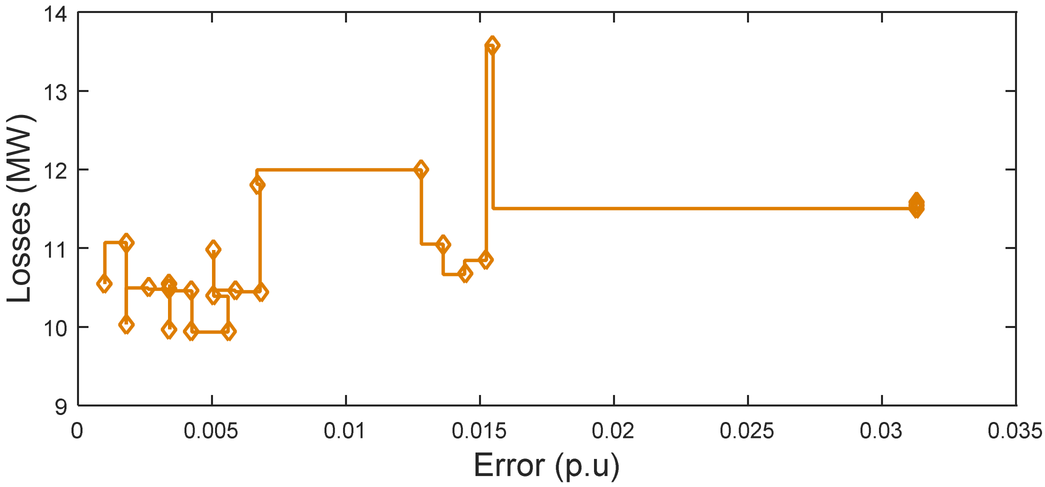


Figure 3. Relation between the losses and the error.

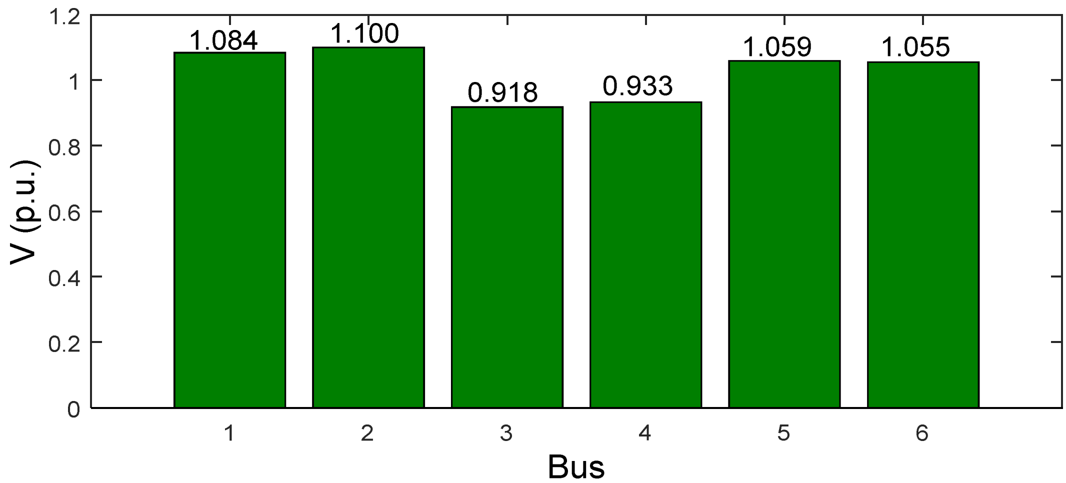


Figure 4 – Voltage results of backpropagation in the IEEE-6 system bus.

Figure 6 is a comparison of four different methods: PowerWorld© (PowerWorld Corporation, 2013), the RBF and the backpropagation with results produced in this work and the PSO in (Prasanthi and Hazeena, 2013). The system built on PowerWorld© for the solution through the Newton-Raphson, taps and reactive values used were the same as backpropagation best scenario in order to obtain losses for comparison with other methods. The values of losses in the RBF and backpropagation (BP) are from the best scenario of 125 training on each architecture.

Tabel 3. Values of the great scenario according to Hopfield and backpropagation.

| Loss MW | Control 3 | Control 4 | Control 5 | Control 6 |
|---|---|---|---|---|
| 0.340 | 0.91 | 0 | 0.91 | 0 |

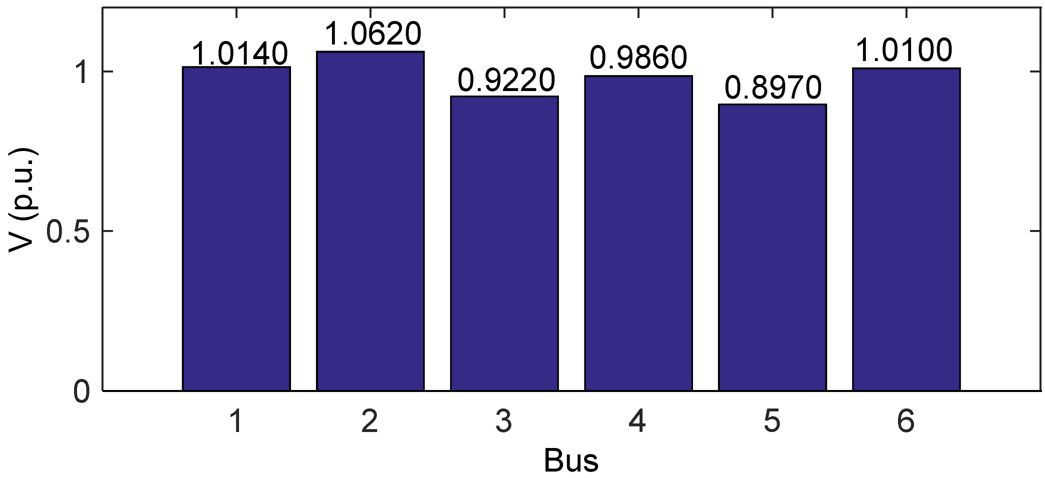


Figure 5 – Voltage results of RBF in the IEEE-6 system bus.

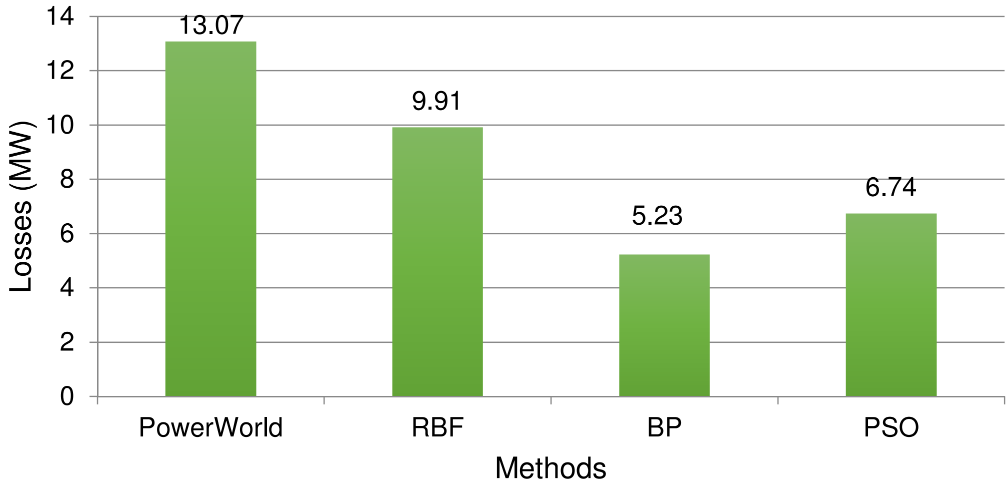


Figure 6. Comparing the methods to the IEEE-6 system bus.

The p.u. voltages calculated in IEEE-6 system bus are shown in Figure 7, where in the scenario with lower loss for ANN is compared to the output of the PSO in (Badar et. al., 2012) and PowerWorld© with the tap and reactive values related to those used in backpropagation scenarios.

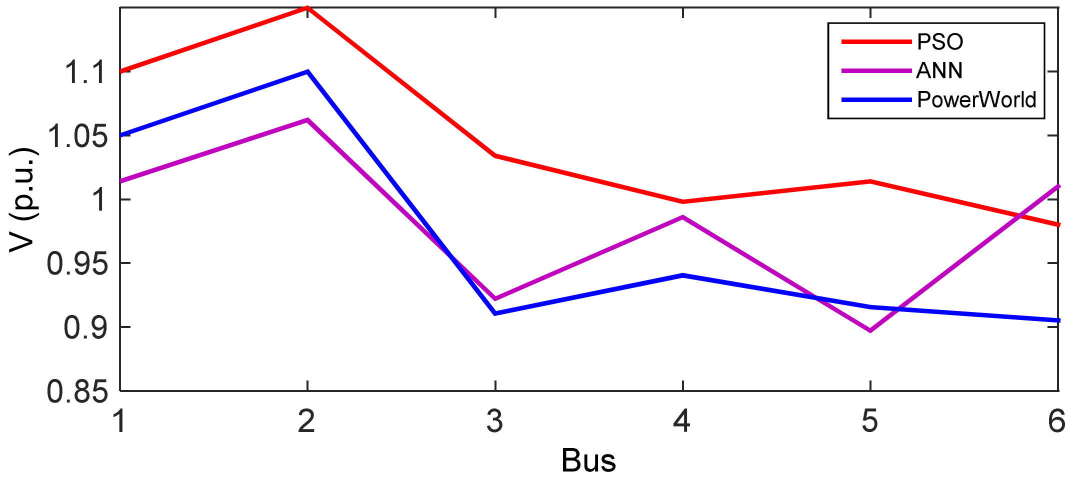


Figure 7. Comparing the voltage in each bus calculated per PSO, ANN e PowerWorld©.

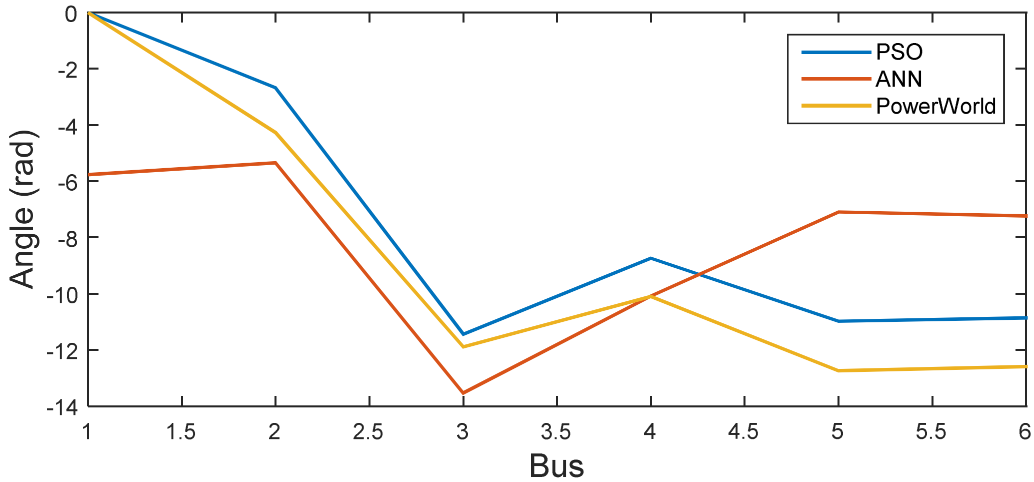


Figure 8. Comparing the angles in each bus calculated per PSO, ANN e PowerWorld©.

Analyzing the Figures 7 and 8, it is possible to note that the curves are parallel and demonstrates the similarity in the results. Only in Figure 8, the buses 1, 5 and 6 of ANN curve portion is more distant from the others, though still parallel on the buses 5 and 6. Because the bus 1 is a reference bus, as well as the PSO, and PowerWorld©, the angle should be 0 rad because the magnitude and angle of the input remain unchanged for the power flow on the solution process.

## 5.2 IEEE-30 System

IEEE-30 system training was conducted for three scenarios: the minimum values, maximum values of all the variables of control and the intermediate values found by the classification criteria using the Time Series Tool. Figure 9 illustrates the voltages in each bus to the backpropagation in the central scenario, resulting from the classification of control data. Note that, in all the voltages magnitudes of the buses are adopted the limits 0.9 p.u. as the minimum and maximum, 1.1 p.u. While Figure 10 shows the relationship between the loss and number of iterations for the IEEE-30. It is observed that the bigger the number of iterations, lower are the losses. This follows from the exhaustive search for the ANN converge and find better results.

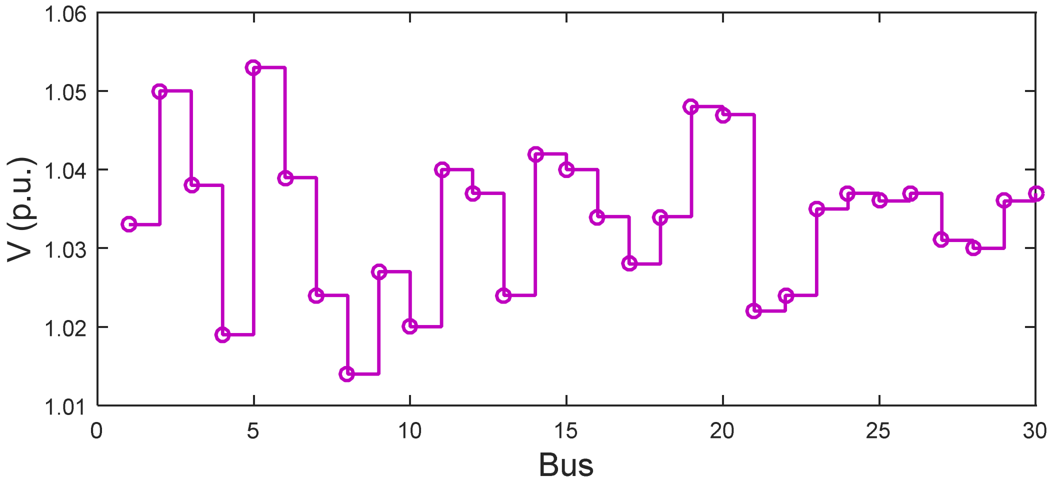


Figure 9. Voltage on the IEEE-30 system bus by the backpropagation.

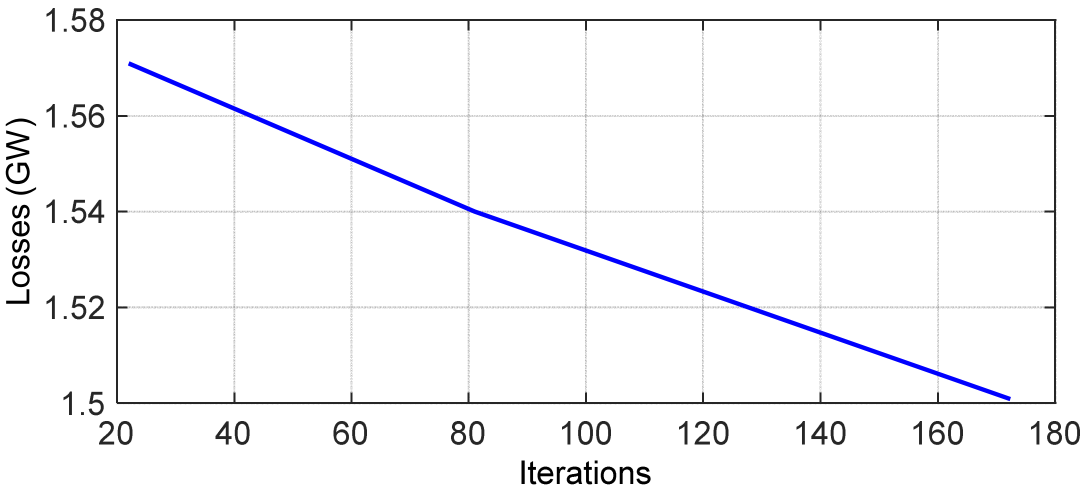


Figure 10. Relation of losses and quantity of iterations on the IEEE-30 system bus.

The architecture with RBF, which has fast convergence, obtained as output controlled voltage with the voltage value in the limit. Despite controlled voltage, the system losses are high due the lack of variation on the variables of control.

## 6 Conclusion

Solving the power flow problem, the Artificial Neural Networks used kind of "black box" in the hidden layers and uses the Equations (5) and (6) for the definition of the ANN input data (other than the Newton-Raphson method, using Equations (3) and (4) exclusively to calculate the voltage and the angle output buses).

Since the convergence time and number of epochs are variables in the NN efficiency, training in the Toolbox of the MATLAB, the backpropagation architecture convergence was obtained after 125 epochs and 34 s. While training in source code, the IEEE 6 bus convergence occurred in 22 epochs and 1 s.

Using the architecture of Hopfield combined with the backpropagation and RBF is possible to ensure that losses can be minimized, but not acceptable. So the training performance of RBF architecture, analyzing the convergence speed, is the best for solving the problem and contribute in electrical system operation centers. The ANN with the backpropagation produces lower losses, however for this search, it is necessary for the operator to repeat sometimes each scenario to reach lower losses. While the RBF, as many times as repeated the training of each scenario, in all them the convergence time will be instantaneous and the loss to the system will be the same.

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