Forecast of Reactive Power Injection in Power Systems Using Artificial Neural Networks

A. de Queiroz, G. G. da Silva and A. Bonini Neto

***Abstract*—Artificial Neural networks (ANN) have proven to be effective tools for estimating current injection in power systems, offering innovative approaches to static voltage analysis. Unlike traditional methods, which involve complex nonlinear load flow equations, ANN allow for the estimation of the reactive power required to ensure the safe operation of electrical systems after a contingency. In this context, this paper employs an ANN to estimate the amount of reactive power that needs to be injected into the system to increase the safe loading margin. The neural network was successfully trained, demonstrating a high estimation capability for samples not included in the training set. The analysis of Q-V and P-V curves, combined with the use of reactive compensation devices such as capacitors and synchronous condensers, is crucial for adjusting active power margins and critical voltage, ensuring system stability. By accurately predicting operating conditions, ANN enable strategic interventions that enhance system resilience and ensure energy efficiency.**

***Index Terms*— Continuation method, Artificial intelligence, Reactive power, Estimation, Loading margin.**

I. Nomenclature

ANN – Artificial Neural Network.
MLP – Multilayer Perceptron.
Y_{des} – Desired Output.
Y_{ob} – Obtained Output.
MSE - Mean Square Error.
CP – Critical Point.
CPF - Continuation Power Flow.
PF - Power Flow.
EPS - Electric Power Systems.
LM - Loading Margin.
TL - Transmission Lines.
ONS - National Electric System Operator.
WSCC - Western System Coordinating Council.

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A. de Queiroz, Department of Electrical Engineering, FE - UNESP, Bauru - SP - Brasil (e-mail: alexandre.queiroz@unesp.br).

G. Gonçalves da Silva, Department of Electrical Engineering, FE - UNESP, Bauru- SP - Brasil (e-mail: giovana.goncalves@unesp.br).

A. Bonini Neto, Department of Biosystems Engineering, FCE - UNESP, Tupã - SP - Brasil (e-mail: alfredo.bonini@unesp.br).

II. Introduction

ELECTRICITY plays a crucial role in the development and progress of modern society, serving as one of the main drivers of socioeconomic development indicators. Reliable access to electricity has become increasingly essential to sustaining contemporary lifestyles, where nearly all daily activities, from work to leisure, directly depend on a stable energy supply [1]. Given this reality, the quality and continuity of electricity supply are not just desirable but necessary to ensure the efficient functioning of the various infrastructures that underpin our society.

In this context, the analysis of security in power systems takes on special significance, as it allows for the identification and mitigation of contingencies that could compromise the safe and stable operation of the electrical system [2]. Through careful analysis of potential adverse events and their consequences, it is possible to anticipate problems and plan corrective actions, ensuring that the system can continue to provide energy reliably, even in unforeseen situations. Therefore, power system security is a fundamental pillar to ensure that electricity remains a driver of socioeconomic development, supporting the growth and sustainability of modern societies.

The P-V (active power vs. voltage) and Q-V (reactive power vs. voltage) curves are indispensable tools for studying power systems, providing a comprehensive analysis of voltage stability and aiding in the identification of safe operational limits to ensure the system's reliability and efficiency [3], [4].

Q-V curves (reactive power vs. voltage) are fundamental analytical tools in the study of power systems. They enable an understanding of the relationship between voltage and reactive power at specific points in a system, providing crucial insights into voltage stability. Essential for the analysis of dynamic system behavior, these curves help identify safe operational limits and predict instability scenarios that could lead to voltage collapse. By visualizing how voltage varies as a function of the available or required reactive power, Q-V curves support strategic decision-making, such as the need for reactive compensation devices. Thus, the analysis of these curves is vital to ensuring the safe and efficient operation of large-scale power systems.

The Western System Coordinating Council [5] requires energy companies to evaluate voltage stability margins using P-V and V-Q analyses, setting a minimum requirement of 5% active power margin for any single contingency situation. In

Brazil, the operational procedures of the National System Operator [6] recommend that, for expansion planning, the stability margin should be at least 6% in cases of single contingencies, following the same criteria established by the WSCC. The criteria for assessing voltage stability, defined by WSCC and also recommended by ONS, are specified in terms of minimum margins for active and reactive power and are categorized into four performance levels (A, B, C, and D). For Level A (single contingency N-1), the Loading Margin (ML) must be greater than 5%. For Levels B and C (double contingencies N-2), the ML should exceed 2.5%. For Level D, which involves the loss of three or more elements, there is no specific loading margin criterion according to ONS. Under normal operating conditions, the symbol N-0 is used.

In this context, this work presents an innovative approach to static voltage analysis, without using nonlinear load flow equations. The goal is to use artificial neural networks to estimate the amount of reactive power needed to ensure that the system operates safely after being subjected to a contingency, based on input data (contingency, percentage met, base case operating point (λ, V) and maximum loading point (λ, V), resistance and reactance of the transmission line). Thus, the aim is to meet criteria established by organizations such as the WSCC.

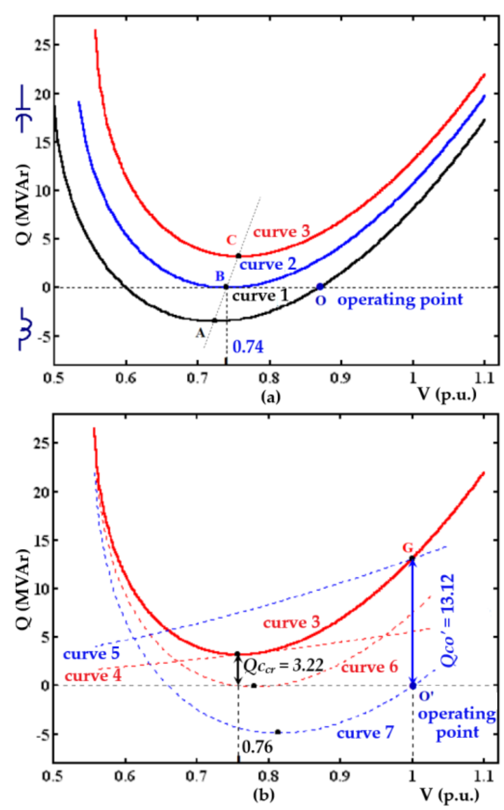
III. P-V AND Q-V CURVES

Fig. 1(a) illustrates the Q-V curves for three loading conditions: curve 1 for P = 50 MW, curve 2 for P_{cr} = 52.681 MW (maximum power with a unit power factor), and curve 3 for P = 55 MW. As active power increases, the QV curve shifts upward. The intersection of the curve with the horizontal axis indicates the system's operating point, and the geometric location of critical points is shown. Only operating points above the critical point are considered stable. The base of the curve (points A, B, and C) defines the voltage stability limit and the minimum required reactive power. Operation is stable to the right of the critical point and unstable to the left of the critical point.

The curves show that the system’s reactive power margin is positive for Curve 1, zero for Curve 2, and negative for Curve 3. For Curve 1, the system can increase active power without requiring local reactive power compensation. For Curve 2, point B represents the maximum active power transfer condition without reactive compensation, indicating the system is at the voltage stability limit. For Curve 3, all points are above the horizontal axis, meaning there are no feasible operating points for this level of loading, and operation can only be restored if reactive power compensation is provided.

To provide the necessary shunt compensation, capacitor banks or static compensators can be used. Fig. 1(b) shows that to increase the maximum power transfer to 55 MW, the required reactive power would be 3.22 MVAr at a voltage of 0.76 p.u. To restore the operating point O’, the required reactive power would be 13.12 MVAr at a voltage of 1.0 p.u. Therefore, to adjust the reactive power for 55 MW to the nominal voltage of 1.0 p.u., the reactive power of the bank needs to be corrected to 5.60 MVAr. The figure also displays the characteristic curves of these banks (curves 4 and 5) and the resulting QV curves (curves 6 and 7). The impact on the maximum power transfer is shown in curves 8 and 9 of Fig. 1(c). Fig. 1(c) also shows an undesirable feature of using shunt compensation through capacitors. As the system's stability margin is increased by adding more compensation, the critical voltage moves closer to the system's normal operating range (shaded area: 0.9 ≤ V ≤ 1.1 p.u.), corresponding to points D, E, and F. Ideally, the critical voltage should be kept as low as possible relative to the minimum operating voltage at the stability limit.

Fig. 1(d) and (e) illustrate the impact of using synchronous compensators on the maximum power point and critical voltage. In Fig. 1(d), curves 10 and 11 represent synchronous compensators with maximum reactive power limits of 5.60 and 13.12 MVAr, respectively. Here, the stability margins are higher, and the corresponding points E' and F' are lower than the previous points E and F. Even with lower reactive powers of 3.22 and 8.70 MVAr, as shown in curves 12 and 13 of Fig. 1(e), the resulting voltages are still lower compared to those with capacitor banks.



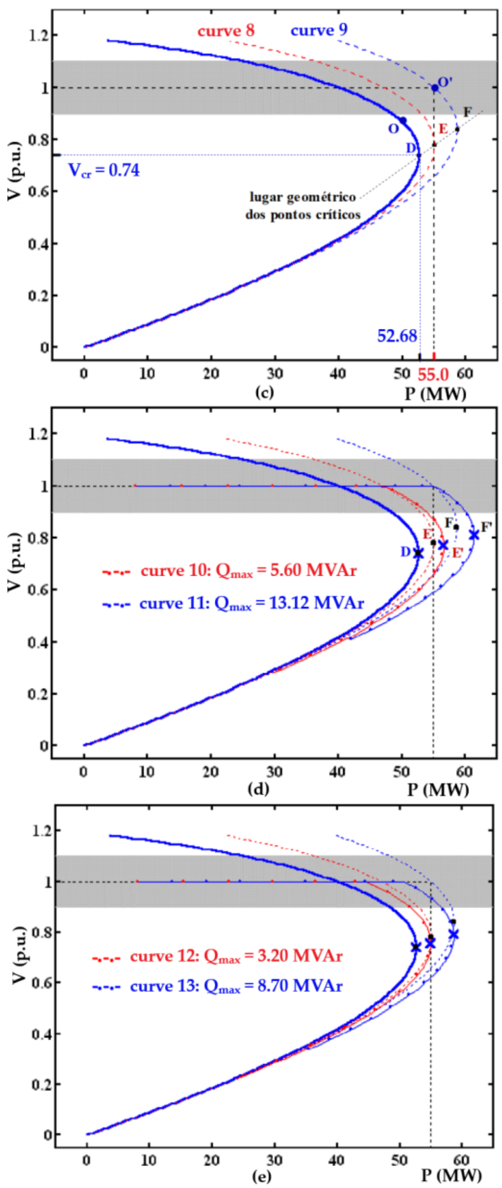


Fig. 1. Effects of reactive compensation on P-V and Q-V curves: (a) Q-V curves, (b) calculation of reactive power for capacitor banks, (c) effect of shunt compensation on active power margin and critical voltage, (d) effect of synchronous compensator on active power margin and critical voltage, (e) effect of changing the limit of the synchronous compensator.

IV. Methodology

The system analyzed in this study is the IEEE 14-bus configuration, as illustrated in Fig. 1. The 1890 samples used for training and validation were obtained using the method described in [4]. Each sample consists of 6 data points: 4 input data for the ANN, which include the loading factor λ, the real and reactive power generated at the slack bus (P_g^{slack} and Q_g^{slack}), and the branch number (transmission lines or transformers); and 2 output data points, representing the total real and reactive power losses of the system.

The IEEE 14-bus system has 20 branches, as shown in Fig. 1. Ninety samples were generated for each branch removed from the system, representing the applied contingency. Removing branch 1 (r1) from the system results in a severe N-2 contingency (double contingency), causing a significant reduction in the system's loading margin, as indicated in the results. The other contingencies are classified as simple (N-1). In this study, the symbol N-0 refers to the system without contingency, that is, the pre-contingency P-V curve (r0).

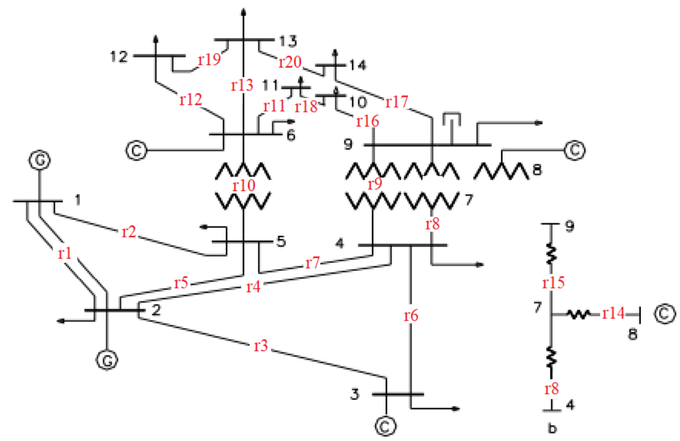


Fig. 1. IEEE 14-bus system with respective branches r.

The Artificial Neural Network (ANN) used was a feedforward multilayer perceptron [14], trained with the backpropagation algorithm [15]. The network structure consists of three layers: an input layer with 4 neurons, a hidden layer with 10 neurons, and an output layer with 2 neurons, as illustrated in Fig. 2. The Matlab® software [16] was employed for both data preparation and results generation.

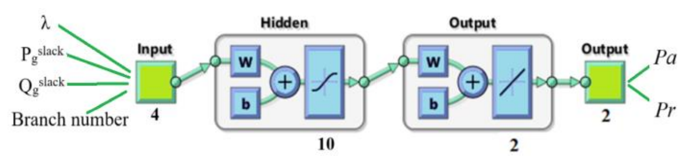


Fig. 2. RNA used in this work.

The value of $\mathbf{u}_k$ (1) represents the sum of the products of the inputs $\mathbf{x}$ by their respective weights $\mathbf{W}$, plus the bias. The bias increases the degrees of freedom, allowing the neural network to better adapt to the provided knowledge.

$$\mathbf{u}_{\mathrm{k}} = \sum_{i=1}^{n} \mathbf{x}_i \, \mathbf{W}_i + \text{bias} \qquad (1)$$

After determining the value of $\mathbf{u_k}$, it is necessary to calculate the activation function $\mathbf{f}(\mathbf{u_k})$ to obtain the output. In this work, the hyperbolic tangent function (2) was used for the hidden layer, while the linear function (3) was employed for the output layer:

$$f(u) = \frac{(1 - e^{-\lambda u})}{(1 + e^{-\lambda u})} \qquad (2)$$

where λ is an arbitrary constant representing the inclination of the curve.

$$f(u) = u \qquad (3)$$

V. RESULTS

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VIII. Biographies

Alexandre de Queiroz. Graduated in Data Processing Technology from the Faculty of Technology of Alta Noroeste in Araçatuba-SP in 2000. PhD student in the Postgraduate Program in Electrical Engineering, São Paulo State University (Unesp), School of Engineering, Bauru, working with Artificial Intelligence via graphical interface applied to predict parameters of electrical power systems. Computer programmer since 1992, the same year he completed the Technical Course in Data Processing integrated into High School. He presents knowledge and research in the area of artificial intelligence, with applications in various areas of knowledge

Giovana Gonçalves da Silva. Degree in biosystems engineering from the São Paulo State University Júlio de Mesquita Filho - FCE -UNESP, Tupã (2021). Postgraduate degree in occupational safety engineering from UNIMAIS (2023). She is currently on a master’s degree in electrical engineering at the São Paulo State University "Júlio de Mesquita Filho" - FEB - UNESP. She is a CAPES fellow in the development of the research project Intelligent systems and mathematical parameterization techniques applied to power flow. She received an honorary mention award for the best work presented at the XXXI CIC UNESP Tupã in 2019.

Alfredo Bonini Neto. Degree in Mathematics (Licentiate) from the Faculty of Dracena - UNIFADRA (2002), and both a master's and doctorate in Electrical Engineering from the São Paulo State University Júlio de Mesquita Filho - FEIS - UNESP, Ilha Solteira (2006 and 2011). He completed his postdoctoral research in 2013 in Electrical Engineering at UNESP - Ilha Solteira, focusing on power systems and mathematical parameterization techniques for solving nonlinear equation systems, aiming at obtaining the critical point and eliminating the singularity of the Jacobian matrix. Currently, he is an Associate Professor at São Paulo State University - UNESP - Tupã Campus. His current research areas include Optimization, Continuation Methods (Parameterization Techniques), and Intelligent Computational Systems applied to Engineering, including Fuzzy Logic and Artificial Neural Networks.