OPTIMIZED VOLTAGE STABILITY FOR MAXIMUM LOADABILITY USING NEURAL NETWORKS

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ABSTRACT: This paper proposes a Neural Network-Based method for on-line maximum loadability estimation, for an optimized power system voltage stability profile. A simulated annealing optimization technique for optimal voltage stability profile through out the whole power network was used. The minimization of the voltage stability index at each individual load bus as well as the global voltage stability indicator is obtained through adjustment of real power and reactive resources control devices. Optimal load buses voltages and angles at the input layer and the maximum MVA loading level at the output layer accomplished the training of the Radial Basis Function Neural Network (RBFNN). The generalization capability of the designed Neural Networks under large number of operation conditions and contingencies has been tested for power systems. Fast performance, accurate evaluation and good prediction for maximum loadadbility level have been obtained.
Results of tests conducted on the Six-bus Wale and Hale system are presented and discussed.

Keywords:
Optimization Technique, Simulated Annealing, Voltage Stability Monitoring, loadability, Neural Networks

1 INTRODUCTION

The power system ability to maintain constantly acceptable bus voltage at each node under normal operating conditions, after load increase, following system configuration changes or when the system is being subjected to a disturbance is a very important characteristic of the system. The non-optimized control of VAR resources may lead to progressive and uncontrollable drop in voltage resulting in an eventual wide spread voltage collapse.

The phenomenon of voltage instability is attributed to the power system operation at its maximum transmissible power limit, shortage of reactive power resources and inadequacy of reactive power compensation tools. A non-optimized setting of the level or control of the reactive resources play an effective role to expedite the voltage instability and to speed up reaching the maximum loading limit.

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The main factors contributing to the voltage collapse are the generators reactive power limit, voltage control limits, load characteristics, reactive compensation devices characteristics and their actions.

Voltage stability estimation techniques based on Jacobian analysis such as, singular value decomposition, Eigenvalue calculations, sensitivity factories, and modal analysis are time consuming for a large power system [1- 4].

Several indices based methods such as Voltage Instability Proximity Index (VIPI) and Voltage Collapse Proximity Indicator (VCPI) are used to evaluate voltage instability. They are based on multiple load flow solutions and give only global picture [5,6]. The transmission proximity index that specifies the weakest transmission part of the system based on voltage phasor approach necessitate the scanning of the whole power system structure for several time which is time consuming approach [7].

The strong tie of the voltage stability problem with the reactive power resources and flow in the system raise the interest in optimizing the rescheduling of the VAR control tools. An optimum VAR picture would maintain a good voltage profile and extend the maximum loading capability of the power network.

Several approaches for optimal reactive power picture have been reported in the literature. Methods such as non-linear programming and linear programming algorithms were applied. They are complex, time consuming and require considerable amount of memory [8 -12].

In order to enhance the voltage stability profile through out the whole power network, simulated annealing (SA) optimization technique [13-14] is applied to control the power elements of major influence on the voltage stability profile. Elements such as generator reactive generation, adjustable shunt compensation devices, transformer tap settings are optimally adjusted at each operating point to reach the objective of increasing the distance from an unstable system state and therefore to increase the maximum possible system safe loading. The objective is achieved through minimizing the highest value of the voltage stability indicator in the whole system and consequently all load buses indicators will follow.

The present work proposes a Neural Network-Based method for an On-line prediction and estimation of steady state voltage stability limit, which is represented in the

form of maximum loadabiltiy while the system, is operating under optimized voltage stability profile.
As an attractive alternative to the Multilayer Perceptron (MLP) Neural Network, an (RBFNN) was designed for maximum loadability level prediction. The advantage of the proposed technique is its fast convergence, its adequate generalization characteristic, and its learning efficiency [15]. The input training information used is the resulting optimal voltage and angles for each load bus covering the whole power system. The output layer information is the maximum value of MVA loading factor before the system collapse.

The constantly changing power network structure, power generation level and the different compensation element and control setting settings dictate a variable maximum loading level
The focus of this work is to develop a practical integrated system capable of on-line real-time estimation or prediction for the maximum loadability while the system is optimally running at a certain operating point. The objective remains the accuracy and fast performance of the developed network.

2 FAST VOLTAGE STABILITY INDICATOR

For voltage stability bus evaluation, an indicator L-index is used. The indicator value varies in the range between 0 (the no load case) and 1 witch corresponds to voltage collapse. The indicator uses bus voltage and network information provided by the load flow program.

For multi-node system

$$I_{bus} = \mathrm{Y}_{bus} \times V_{bus} \tag{1}$$

By segregating the load buses (PQ) from generator buses (PV), equation (1) can write as

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} H_1 & H_2 \\ H_3 & H_4 \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{3}$$

V_L, I_L: Voltages and Currents for PQ buses
V_G, I_G: Voltages and Currents for PV buses
Where, H_1, H_2, H_3, H_4: submatrices generated from Y_{bus} partial inversion.
Let

$$\overline{V}_{ok} = \sum_{i=1}^{n_G} H_{2ki} \cdot \overline{V}_i \tag{4}$$

n_G: number of generators

$$H_2 = -Y_1 \times Y_2 \tag{5}$$

$$L_K = \left| 1 + \frac{V_{ok}}{V_K} \right| \tag{6}$$

L_k: L-index voltage stability indicator for bus k [16,17]

Stability requires that $L_k < 1$ and must not be violated on a continuous basis. Hence a global system indicator L describing the stability of the complete system is $L = L_{max}\{L_k\}$, where in $\{L_k\}$ all L bus indexes are listed.
In practice L_{max} must be lower than a threshold value. The predetermined threshold value is specified at the planning stage depending on the system configuration and on the utility policy regarding the quality of service and the level of system decided allowable margin. In practice, the calculation of the complex vector V_{ok} never uses the inversion of Y_1.

$$[-Y_1] \cdot V_{ok} = [Y_2] \cdot V_G \tag{7}$$

Instead sparse factorization vector methods have been used to solve the linear system (7) and make from L-index a potential candidate for real-time performance.

3 SIMULATED ANNEALING TECHNIQUE

3.1 Overview

Simulated annealing is an optimization technique that simulates the physical annealing process in the field of combinatorial optimization. Annealing is the physical process of heating up a solid until it melts, followed by slow cooling it down by decreasing the temperature of the environment in steps. At each step, the temperature is maintained constant for a period of time sufficient for the solid to reach thermal equilibrium.
Metropolis et al [13] proposed a Monte Carlo method to simulate the process of reaching thermal equilibrium at a fixed value of the temperature *T*. In this method, a randomly generated perturbation of the current configuration of the solid is applied so that a trial configuration is obtained. This trial configuration is accepted and becomes the current configuration if it satisfies an acceptance criterion. The process continues until the thermal equilibrium is achieved after a large number of perturbations. By gradually decreasing the temperature *T* and repeating Metropolis simulation, new lower energy levels become achievable. As *T* approaches *zero* least energy configurations will have a positive probability of occurring.

3.2 SA Algorithm

At first, the analogy between a physical annealing process and a combinatorial optimization problem is based on the following [14]:

- Solutions in an optimization problem are equivalent to configurations of a physical system.
- The cost of a solution is equivalent to the energy of a configuration.

In addition, a control parameter C_p is introduced to play the role of the temperature T.

The basic elements of SA are defined as follows: -

- ***Current, trial, and best solutions,*** x_{current}, x_{trial}, and x_{best}: these solutions are sets of the optimized parameter values at any iteration.
- ***Acceptance criterion***: at any iteration, the trial solution can be accepted as the current solution if it meets one of the following critera; **(a)** $J(x_{\text{trial}}) < J(x_{\text{current}})$; **(b)** $J(x_{\text{trial}}) > J(x_{\text{current}})$ and $exp(-(J(x_{\text{trial}})-J(x_{\text{current}}))/C_p) \geq rand(0,1)$. Here, $rand(0,1)$ is a random number with domain [0,1] and $J(x_{\text{trial}})$and $J(x_{\text{current}})$ are the objective function values associated with x_{trial} and x_{current} respectively. Criterion (b) indicates that the trial solution is not necessarily rejected if its objective function is not as good as that of the current solution with hoping that a much better solution become reachable.
- ***Acceptance ratio***: at a given value of C_p, an n_1 trial solutions can be randomly generated. Based on the acceptance criterion, an n_2 of these solutions can be accepted. The acceptance ratio is defined as n_2/n_1.
- ***Cooling schedule***: it specifies a set of parameters that governs the convergence of the algorithm. This set includes an initial value of control parameter C_{p0}, a decrement function for decreasing the value of C_p, and a finite number of iterations or transitions at each value of C_p, i.e. the length of each homogeneous Markov chain. The initial value of C_p should be large enough to allow virtually all transitions to be accepted. However, this can be achieved by starting off at a small value of C_{p0} and multiplying it with a constant larger than 1, α, i.e. $C_{p0}=\alpha C_{p0}$. This process continues until the acceptance ratio is close to 1. This is equivalent to heating up process in physical systems. The decrement function for decreasing the value of C_p is given by $C_p=\mu\, C_p$ where μ is a constant smaller than but close to 1. Typical values lie between 0.8 and 0.99 [14].
- ***Equilibrium condition***: it occurs when the current solution does not change for a certain number of iterations at a given value of C_p. It can be achieved by generating a large number of transitions at that value of C_p.
- ***Stopping Criteria***: these are the conditions under which the search process will terminate. In this study, the search will terminate if one of the following criteria is satisfied: **(a)** the number of Markov chains since the last change of the best solution is greater than a prespecified number; or, **(b)** the number of Markov chains reaches the maximum allowable number.

4 RADIAL BASIS FUNCTIONS NEURAL NETWORKS

Radial basis functions neural networks (RBFNN) have been developed based on the theory of RBF approximation for real multivariable function approximation [18]. The use of RBFNN in engineering applications is increasing rabidly. RBFNN provide a powerful tool for constructing nonlinear mappings form input-output data. Moreover, RBFNN has the advantage of easy and effective learning algorithm compared to other multilayer feedforward Neural Networks. The attractive feature of the RBFNN lies in the linear dependence in the parameters, which greatly simplifies the design and analysis of such networks. A typical multi-input multi-output RBFNN is shown in Figure 1, which consists of three layers. An input layer with n inputs, one hidden layer with m neurons, and an output layer with k output units. Each output unit in the RBFNN performs the following function

$$y_i(x) = \sum_{j=1}^{m} w_{ij}\phi_j(x) \quad ; i = 1,2,\ldots,k \tag{8}$$

Where $\phi_j(x)$'s are radially symmetric functions representing the nonlinearities in the hidden layer. The most commonly used function is the Gaussian function given by

$$\phi_j(x) = \exp\left(\frac{-(x-\hat{x}_j)^2}{2\sigma_j^2}\right) \tag{9}$$

The Gaussian function is defined by a center position $\hat{x}_j$ and a width σ_j. The center of the basis function can be determined by simple heuristic approaches such as the k-means clustering method, and the width can be determined using nearest neighbor method [19,15]. The number of hidden units can be selected as the number of training patterns. This approach often leads to very large networks and poor generalization capabilities. Different approaches have been proposed for the selection of the number of hidden units [20,21]. The weights from hidden to output layers can be
Computed using the least mean square (LMS) or pseudo inverse methods.

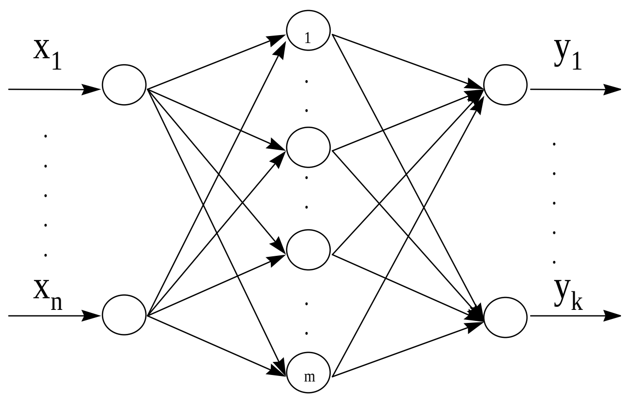

Figure 1: Radial Basis Function Neural Network

5. SIMULATION RESULTS AND DISCUSSIONS

The test is conducted on Ward and Hale Six bus power system [23]. The proposed Neural Network has 8 inputs representing the voltage and angle of each load bus in the system and one output corresponding to the maximum loadability factor. Only the optimized load bus voltages and their angles are considered at input layer. The Voltage stability indicator L-index corresponding to the slack bus and to the voltage-controlled bus are always zeros as long as long as the bus voltage remains controlled. The optimized inputs voltages and their corresponding angles values are based on minimizing the highest voltage stability index L_{max} of the whole system.

The input out training sets were covering random line contingencies, random variation of voltage-controlled buses between 0.95 and 1.1 per unit as well as random real power generation.

The training was performed using the solverb function in the MATLAB Neural Networks toolbox. The estimation error of the maximum voltage stability loadability factor for the training data is shown in Figure 2. The obtained error for the whole range of training sets is found to vary between 0.0122 and –0.0156 witch corresponds to 0.66% to – 0.85%

To the generalization capabilities of the proposed Neural Network, an investigation was conducted by using 200 patterns outside and from both left and right of the training range. The results obtained are shown in Figure 3.

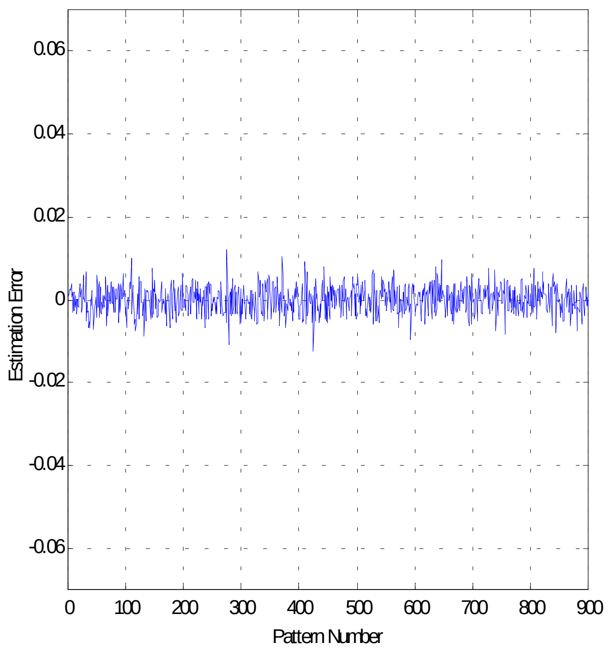

Figure 2: Six-bus maximum loading Factor Estimation error for the testing data

The percentage error for the testing case varies between 0.74% to –2.09% which shows and proves the ability of the proposed Neural Network to predict the loadability factor indices for new patterns with very good accuracy.

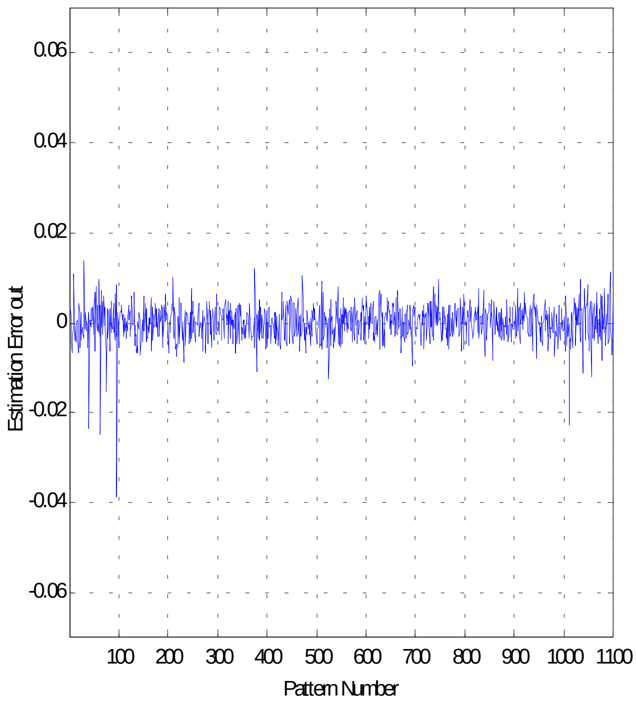

Figure 3: Six bus maximum loading Factor Estimation error for the testing data

6. CONCLUSIONS

This paper proposed a prototype Radial Basis Function Neural Network (RBFNN) developed for a practical integrated system capable of on-line real-time estimation or prediction for the maximum loadability while the system is optimally running at a certain operating point. The application conducted on the test system has demonstrated accuracy and efficiency. The designed (RBFNN) was able to follow a non-linearities introduced by line contingencies and changes in the power network random behavior. To learn the power system characteristic in conjunction with voltage stability optimal profile, the proposed network did not have to map the power system structure in order to reach the generalization capability. The fast performance of the network proves its strong candidacy for being an effective and essential part for an integrated On-line maximum loaddability prediction system.

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7 ACKNOWLEDGEMENT

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