ESTIMATING THE VOLTAGE COLLAPSE PROXIMITY INDICATOR USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Modern power systems are currently operating under heavily loaded conditions due to various economic, environmental, and regulatory changes. Consequently, maintaining voltage stability has become a growing concern for electric power utilities. With the increased loading and exploitation of the power transmission system, the problem of voltage stability and voltage collapse attracts more and more attention. A voltage collapse can take place in systems and subsystems, and can appear quite abruptly. There are different methods used to study the voltage collapse phenomenon, such as the Jacobian method, the voltage instability proximity index (VIPI) and the voltage collapse proximity indicator method. This paper is concerned with the problem of voltage stability, and investigates a proposed voltage collapse proximity indicator applicable to the load points of a power system. Voltage instability is early predicted using artificial neural networks on the basis of a voltage collapse proximity indicator. Different system loading strategies are studied and evaluated. Test results on a sample and large power system demonstrate the merits of the proposed approach. The objective of this paper is to present the application of ANN in estimating the voltage collapse proximity indicator of a power system.

KEYWORDS: Power Systems, Voltage Security, Voltage Instability, Voltage collapse and Neural Networks

1. INTRODUCTION

Progressive energy demands associated with shortage in installed capacities have resulted in the power systems to be operated at or close to their security limits.

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These limits are, generally, related to the problems of thermal loading and transient stability. Modern control and protection equipment have raised the transfer limits in stability limited systems. However, as the operating conditions for large power systems have evolved, a new type of problem has been observed. This phenomenon is referred to as voltage instability or voltage collapse [1-5]. It is characterized by a continuous decline of voltage, which can occur due to the inability of the network to meet the increasing demand for reactive power.

Available methods for voltage stability assessment are usually classified into static and dynamic methods [4]. Static methods assume a steady state model or a linearized dynamic model to investigate the state of the equilibrium point of a specified operating condition of the power system. For Dynamic methods, the solution of the governing equations is carried out in the time domain and the study period is in the order of several minutes. Dynamic simulations are time consuming and do not readily provide sensitivity information and degree of stability. A number of indices of static voltage stability have been proposed in literature to quantify the proximity of the power system to voltage collapse. Among the most widely used voltage stability indices are the voltage collapse proximity indicator [3,5], the minimum singular value of the power flow Jacobian matrix [6], and loading margin [7].

Voltage collapse proximity indicators are usually considered as useful measures of the closeness of the power system to the collapse point. For a particular operating point, the value of the indicator provides information of each bus voltage and its proximity to the voltage collapse limits. However, as the operating condition of a power system continuously changes, it is difficult to use these methods to provide real time information due to the significant computational requirements of such methods. Artificial Neural Networks (ANN) computational schemes have been successfully applied in loading margin estimation [7], optimization of electrode contour [8] and security assessment [9]. ANN with their ability to provide non-linear input/output mapping, generalization, and abstraction [10] have the potential to estimate the voltage collapse proximity indicator of a power system without solving the governing power system equations.

The objective of this paper is to present the application of ANN in estimating the voltage collapse proximity indicator of a power system. The multilayer feedforward ANN with the backpropagation method is utilised. With the input /output patterns being known apriori, supervised learning is employed for training the network. Some of the methods available for estimating the proximity-to-collapse indicator of a power system are briefly summarised. The structure of the proposed neural network is also presented. Test results based on a simple power system are presented to illustrate the suitability of the proposed method.

2. METHODS TO ESTIMATE VOLTAGE COLLAPSE INDICATORS

Different indicators have been proposed to assess the proximity of the system to voltage collapse.

2.1 The Jacobian Method

This method was the first to relate power system stability to the load flow Jacobian. In this work, it is shown that, with some assumptions (P and V are specified for all generator buses, neglecting damping for all of the generators) and using Newton-Raphson method in the polar form, the determinant of the load flow Jacobian becomes equal to the product of the eigenvalues of the system. This means that when a change takes place in the sign of the determinant, at least one of the Eigen values has crossed the imaginary axis from the stable to the unstable side [1,6].

2.2 Voltage Instability Proximity Index

Power flow equations typically present multiple solutions, with one of these solutions corresponding to an “operable” point of a power system [5]. It is known that the number of existing solution decreases as operating point approaches the collapse point and only a pair of solutions remain near the collapse point and then coalesces on it. The Voltage Instability Proximity Index (VIPI) is used to predict proximity to voltage collapse using this solution pair.

2.3 Voltage Collapse Proximity Indicator

The Voltage Collapse Proximity Indicator (VCPI) was introduced by Kessel and Glavitch [3] for a two-bus system model and was generalized for a multi node system using a hybrid model for the power system. This indicator utilizes the information obtained from a normal load flow solution. The method can be used to determine local indicators corresponding to each load bus. The indicator L varies in the range between 0 (no load of system) and 1 (voltage collapse) values close to one indicate proximity to power flow divergence. Based on the concept, various models are derived which allow the predicting of voltage instability or the proximity of a collapse under various contingencies such as loss of generators or lines as well as load variations. The advantage of the method lies in the simplicity, reliability and it can give a good indication about the critical power a system can maintain before collapse over the whole region and for all the cases studied. A local indicator L_j for each node j can be calculated [3] by:

$$L_j = \left| S_j^+ / (Y_{jj}^{+*} . V_j^2) \right| \tag{1}$$

Where Y_{jj}^+ (Transformed admittance)= $(1/Z_{jj})$, V_j: consumer node voltage ,

S_j^+: transformed power = $S_j + S_j^{cor}$,

And S_j^{cor} is given by :

$$S_j^{cor} = [\sum_{i \in \alpha_L} (Z_{ji}^* / Z_{jj}^*).(S_i / V_i)].V_j \tag{2}$$

And α_L is the set of consumer nodes.

Therefore V_j is affected by the nodal power S_j and an equivalent power S_j^{cor}, which stems from the other loads of the system.

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For stable situations the condition $L_j \le 1$ must not be violated for any of the nodes j.

Hence a global indicator L describing the stability of the complete subsystem is given by Eq. (3)

$$L = \underset{j \in \alpha_L}{Max} \; (L_j) \tag{3}$$

One way of determining

$$L_j = \left| L_j \right| = \left| 1 - \frac{\sum_{i \in \alpha_G} C_{Ji} V_i}{V_j} \right| \qquad j \in \alpha_L \tag{4}$$

Where α_L: set of load buses, α_G: set of generator buses, V_j: complex voltage at load bus j, V_i: complex voltage at generator bus I, and C_{ji}: element of matrix C determined by:

$$[C] = -[Y_{LL}]^{-1}[Y_{LG}] \tag{5}$$

Where $[Y_{LL}]$ and $[Y_{LG}]$ are submatrices of the Y bus matrix.

The important outcome of the presented theory is $L < 1$ for stability to be guaranteed. This theory is exact when two conditions are fulfilled:

1- All generator voltages remain unchanged, amplitude and phase wise.

2- The nodal currents respond directly proportional to the current I_j and indirectly proportional to the voltage V_j at the node j under consideration. The drawback of this method is that it fails to consider the operating constraints of system equipment, such as the VAR limits of the generators. This is an important consideration because when a generator reaches its VAR limit the terminal voltage can no longer be controlled. Under this condition, the machine model has to be modified resulting in a change in the system performance pattern [12].

In order to determine the voltage collapse proximity indicators, several alternate loading strategies were suggested in literature [3,7]. These include, either increasing

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all real/reactive power generation and load of the system by a constant factor [3], or increasing real and reactive power of all loads and only the active power of the generators [7]. In this work, all possible alternatives of increasing the system loading are studied and assessed. It was found that when the load is increased on only load buses, the system becomes closer to voltage instability than any other case; i.e. the voltage collapse proximity indicator is the highest of all other cases. Accordingly, this strategy is followed in the neural network application. The loads are increased by a constant Loading Factor (LF) in accordance with the following expressions:

$$P_L = P_{Lo} . LF \tag{6}$$

$$Q_L = Q_{Lo} . LF \tag{7}$$

Where LF is the Loading Factor, P_{L0}, Q_{L0}, P_L and Q_L are the initial and increased active and reactive powers of a load bus.

3. THE ARTIFICIAL NEURAL NETWORK MODEL

In recent year ANN's have been proposed as an alternative method for solving certain difficult power system problems where the conventional techniques have not achieved the desired speed, accuracy, and efficiency. The ANN consists of an input layer, an output layer, and at least one hidden layer; each layer consists of a set of neurone similar to Fig.1. The neurones are interconnected. It is a feedforward network composed of an organized topology of interconnected processing elements (PE) called neurones or nodes. Nodes of each layer are fully connected to those of the succeeding layer through connection weights. The input layer serves only to transfer the input information without processing to the next layer. The PE, of any other layer, transfers its input according to:

$$X_i^{[k]} = f\{\sum W_{ij}^{[k]} X_j^{[k-1]}\} = f[i_i^{[k]}] \tag{8}$$

Where X_i is the output of the i-th PE in the k-th layer. $X_1^{[k-1]}, X_2^{[k-1]}, \ldots, X_n^{[k-1]}$ are n outputs form preceding layer and

$W_{i1}^{[k]}, W_{i2}^{[k]}, \ldots, W_{in}^{[k]}$ are weight connections between k-1 and k-th layer. The transfer function f can be a sigmoid or hyperbolic tangent function. With supervised learning, pairs of input – output data are present to the network at both the input and output layers. The input data flow from the input to the output layer through the hidden layers. At the output layer the error between the desired and computed value is determined. The error is back propagated and weights adjusted according to the gradient decent technique [10].

The whole procedure is repeated until the Root Mean Square error (RMS) at the output layer falls below a small-prespecified value, usually between 0.1 and 0.01. The RMS error is obtained by summing squares of the errors for each PE in the output layer, dividing it by the number of PE, and taking the square root of the average. Weight connections are randomly generated between – 0.1 and 0.1 at the initiation of the learning phase. Learning and momentum coefficients, η and γ are incorporated in weight adjustment to speed up the convergence process while reducing error oscillations. Input –output data are usually scaled between 0 and 1 or –1 and 1 depending on the type of the transfer function employed. To test the trained network generalization ability, the Mean Absolute Error (MAE) defined below, is used [8]

$$MAE = (1/N_m N_K)\Sigma\Sigma\{\left|t_{PK} - o_{PK}\right|/t_{PK}\}100 \quad (9)$$

Where p varies between 1 and N_m and N_m is the number of patterns, N_K is the number of neurons in the output layer, t_{PK} is the target output of neuron k and o_{PK} is its calculated output.

4. PROPOSED METHOD

The purpose of the neural network proposed in this research is to map the relationship between the operating conditions of a power system and the corresponding voltage collapse proximity indicator. The employed neural network consists of an input layer, one hidden layer, and output layer. The input to the network is measurable parameters of the power system like generator terminal voltage and real and reactive power generation/load. The outputs of the neural network are the voltages; and indicators of all load buses. As mentioned earlier, such indicators provide early detection of a possible voltage collapse of the power system. Numerous simulations using developed load flow software are carried out to obtain the training data required for the neural networks. For this study, the real and reactive power limits of the generator have been set to the maximum values. The loads have been modeled as constant power loads. It is assumed that all the loads increase by a constant loading factor, maintaining the same power factor as in the base case. However, the proposed method is general such that suitable models for generators, converters, regulating transformers, phase shifters etc., and their limits can be used and the training data can be generated. Similarly, only the maximum voltage collapse indicator can also be used as the output of the neural network instead of specifying the load voltages with their corresponding indicators.

5. APPLICATION TO A SAMPLE POWER SYSTEM AND RESULTS

The proposed method has been tested using a 5-bus system shown in Fig.2. The system has two generators on buses 1, 2 and loads on buses 2, 3, 4, and 5 [11]. For different sets of input parameters, numerous simulations are performed to generate the necessary training data. For each distinct operating condition, the corresponding load buses voltages as well as their indicators have been determined. Specifically, for the 5-bus system, the input to the neural network consists of real/reactive power generation and load and the generator terminal voltage. The input/output training patterns used for the learning phase of the ANN are given in Table 1. A total of 26 patterns with 0.1 step loading factor started with LF equal 1 and ended at 3.18, are used for training the network. All data are in per unit on a base of 100 MVA. The training data input/output patterns are presented to the ANN during the learning phase. Commercially available ANN software implementing the back-propagation method is used. The neural network has 12 inputs (the net real and reactive power at buses 2, 3, 4 and 5 and voltage magnitudes at buses 1 and 2), 9 hidden neurons, and 6 outputs (the voltage magnitudes at the load buses V3, V4 and V5, and their corresponding indicators L3, L4 and L5) as tabulated in Table1. It is obvious from the output vector in Table1, that bus 5 is the weakest bus where the indicator L5 has the highest value for different values of loading factor, as it is equal to 0.076 at unity LF, while L3 and L4 values at the same LF are 0.062 and 0.065 respectively. At 3.18 LF, L5 is 0.802 while L3 and L4 are 0.469 and 0.517. Therefore for this sample system, weakest buses ranked as bus 5, then bus 4 and finally bus 3. Convergence of the learning process is shown in Fig.3. Both the coefficients of learning η and momentum γ have the same value (0.84) for accurate and fast results. The RMS error is less than 0.01% as the number of iteration reaches 5527. In order to test the trained network generalization ability, 12 new patterns are generated and presented to the network. It is found that the misclassification is almost 0% if the results are compared with the actual results (Table 2). Also it is found that the accuracy obtained with the ANN is quite reasonable. The ANN correctly predicted the highest voltage collapse indicator corresponding to the weakest bus (bus 5). Fig. 4 and Fig. 5 shows the performance of the ANN in predicting the highest indicator as well as the decline in the voltage associated with bus-5. Comparison of the ANN and actual results for bus 5 and the behavior of the associated indicator demonstrate the efficiency and accuracy of the proposed approach. The calculated value of MAE in the test results is about 0.0174 for 9 neurons of the hidden layer. And for 6 neurons of the hidden layer the MAE is 0.0106, while for 12 neurons this value is reduced to 0.0103.

6. ANALYSIS OF EXPECTED METHOD PERFORMANCE UNDER COMPLEXITY OF LARGE PRACTICAL POWER SYSTEM

The proposed large practical power system has been tested using a 14-bus system. The system has 4 generators on buses 2, 3, 6, 8 and from bus 2 to bus 14 are load buses. For different sets of input parameters, numerous simulations are performed to generate the necessary training data. For each distinct operating condition, the corresponding load buses voltages as well as their indicators have been determined. The input to the neural network consists of real/reactive power generation and load and the generator

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terminal voltage. A total of 18 patterns with 0.05 step loading factor started with LF equal 1 and ended at 1.85, are used for training the network. All data are in per unit on a base of 100 MVA. The training data input/output patterns are presented to the ANN during the learning phase. The neural network has 35 inputs, 33 neurons in the hidden layer, and 26 outputs. Bus 14 is the weakest bus where the indicator L14 has the highest value for different loading conditions. The coefficient of learning η is (0.5) and momentum γ is (0.7) for accurate and fast results. The RMS error is less than 0.07% as the number of iteration reaches 3686. In order to test the trained network generalization ability, 17 new patterns were generated and presented to the network. It is found that the accuracy obtained with the ANN is quite reasonable. The ANN correctly predicted the highest voltage collapse indicator corresponding to the weakest bus (bus 14). Fig.6 show the comparison of actual voltage and ANN voltage. The calculated value of MAE in the test results is about 0.0008.

7. CONCLUSIONS

In this paper ANN approach for early prediction of the proximity to voltage collapse in a power system has been proposed. The ANN is trained based on the data obtained from numerous simulations. This technique is applicable to use for on-line estimation of stability margin from system voltage collapse. The indicator L has a very simple structure, can be handled easily and can be extended to multi-node system. The data as well as the results presented indicate the possibility of using the technique for on-line voltage stability prediction especially for practical power system in comparison with real simulation where large computation time is required. The information delivered by the trained network should be useful in early prediction of the voltage collapse phenomena in a power system. The proposed approach has the potential to be a useful tool for fast real time voltage security assessment in a power system.

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حساب مؤشر انهيار الجهد باستخدام شبكات الخلايا العصبية

نظم القوى الكهربية الحديثة مصممة للعمل تحت ضغط عالى نتيجة للتغيرات الاقتصادية ، ومع زيادة الأحمال تظهر مشكلة هامة وهى ظاهرة انهيار الجهد ، ولذلك تتركز مشكلة هذا البحث على ظاهرة انهيار الجهد فى نظم القوى الكهربية ، لذا تم استعراض بعض الطرق المستخدمة لحساب استقرار الجهد وهى : 1- استخدام مصفوفة نيوتن رافسون فى دراسة تتبع الأحمال لإيجاد قيم معينة .

2- مبين عدم استقرار الجهد . 3- مؤشر ظاهرة انهيار الجهد .

وتم استخدام شبكات الخلايا العصبية فى دراسة ظاهرة انهيار الجهد وذلك بتطبيقها على نظام مبسط وأخر كبير وتم تحليل النتائج المستخلصة وعمل المقارنات المختلفة بين الطريقة المقترحة والطرق الأخرى المستخدمة من قبل ، ووجد أن النتائج تكاد تكون متطابقة وان نسبة الخطأ فى النظام المبسط

0.0174 % وفى النظام الكبير 0.083 % وبالتالى تم الحصول على صورة كاملة لحالة الجهد بطريقة مبسطة مع الوقاية اللازمة لمنع هذا الانهيار فى الجهد قبل حدوثه.

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