STEADY–STATE VOLTAGE COLLAPSE PREDICTION AND CORRECTION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

Voltage stability is one of the major concerns in the operation and control of modern power systems. Information such as voltage weak buses/critical voltage is becoming very important to voltage stabilization and control of modern power systems. In this paper Artificial Neural Network is applied for finding the critical voltage i.e., near voltage collapse and the value of the shunt capacitor banks to be inserted at the load bus for increasing its voltage by 10 percent as countermeasure against voltage collapse . This gives the operator an on–line fast action, the values of the shunt capacitor banks to be inserted at that load bus which lead to increasing in its voltage and prevent from total voltage collapse.

Keywords: Power System,Voltage Collapse, Artificial Neural Network.

1. Introduction

Voltage collapse in electric power systems has received significant attention in the literature[6-9]. This research has been motivated by increases in power demand which result in operation of electric power system near their stability limits. So, voltage collapse typically occurs on power systems which are heavily loaded, faulted and/or have reactive power shortages. Voltage collapse is a system instability in that it involves many power system components and their variables at once. Indeed, voltage collapse often involves an entire power system, although it usually has a relatively larger involvement in one particular area of the power system. Voltage collapse is associated with the reactive power demands of loads not being met because of limitations on the production and transmission of reactive power. The primary limitations on the transmission of reactive power are the high reactive power loss on heavily loaded lines and line outages. There are several power system changes known to contribute to voltage collapse:

- Increase in loading
- Generators or Static Var Compensator (SVC) reaching reactive power limits
- Action of tap changing transformers
- Line tripping or generator outages

Most of these changes have a large effect on reactive power production or transmission. Control actions such as:
1-Switching in shunt capacitors
2-Blocking tap changing transformers
3-Redispatching of generation
4-Rescheduling of generator and pilot bus voltages
5- Secondary voltage regulation
6- Load shedding and temporary reactive power overload of generators are countermeasures against voltage collapse.

The objective of applying ANN to voltage stability analysis is to make fast on–line prediction of voltage instability of the system [5] and taking a control actions to prevent voltage collapse. In conventional technique, a lot of calculations are involved which take a long time to take an action for preventing voltage collapse. ANN is trained by sets of off-line simulation results that indicate whether the voltage is stable or critically stable. In this approach, a Voltage Collapse Proximity Indicator based on the P-V curve method that depends on load flow calculation is used. The ANN training set input patterns are obtained by increasing the power P-Q (for a proposed power system) at the load bus for a different power factors and calculating the critical voltages. Then, shunt capacitor bank are calculated

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to increase the voltage at that load bus by 10 percent as countermeasure against voltage collapse. Finally, ANN is tested for unseen cases and the results are very encouraging .

2-Methodology:P-V Curve Method:

This method determine steady-state loadability limits which are related to voltage stability. Power flow program is used for analysis. This method is applied on a proposed power system as given in figure 1 for different power factors. For each power factor, the power increases at the load until the verge of voltage collapse, v_{cr} (maximum loadability). At more leading power factors the maximum power is higher (leading power factor is obtained by shunt compensation). The critical voltage is also higher, which is a very important aspect of voltage stability.

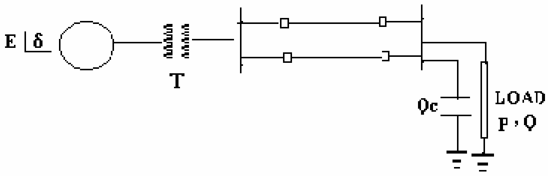

Figure 2: Proposed Power System

3-Neural Network And Voltage Collapse

3.1 Artificial Neural Network

Artificial Neural Networks (ANNs) simulate the human intelligence and are characterized by a robust generalization and error tolerance found in human beings. They can discern patterns and relationships that are beyond the capabilities of the numerical methods such as regression and pattern recognition. The biological brain is the nerve cell or neuron that acts as a simplified numerical processing. In fact, the brain contains billions of such neurons, all heavily interconnected and operating in parallel. In ANN, such interconnections are known as weights that connect neurons in different layers. The ANN used in this paper is the three-layer Multiple Layers Perceptron (MLP) network as shown in Figure 2. The MLP network used here consists of one input layer, one hidden layer, and one output layer. The learning algorithm of the MLP uses back propagation. The error, which is the difference of the ANN output and the desired response, is calculated and propagated backwards from the output to hidden layer, and then to the input. This is done by minimizing an error function as follows:

$$E = \sum_P E_P = \frac{1}{2}\sum_P \sum_K (t_k^P - O_k^P)^2 \qquad (1)$$

where t_k is the desired output and O_k is the predicted output of the neural network. Each weight is changed according to the rule

$$\Delta w_{ij} = -k\frac{dE}{dw_{ij}} \qquad (2)$$

where k is a constant of proportionality, E is the error function, and w_{ij} represent the weights of the connection between neuron j and neuron i. The process is repeated until the difference between all output nodes (predicted) and all patterns(desired outputs) are within some accepted tolerance.

ANNs are characterized by two steps known as *training* and *testing*. During *training*, weights are modified in a manner that causes the desired input/output relationship to be learned as shown in Figure 3. The training set is shown to the network many times (iterations or epochs), until converge is obtained. Currently, no general guidelines for determining a priori which combination of neurons/hidden layers (architecture) will perform best for a given problem, only trial-and-error is used. Thus, the choice can improve or degrade the network performance. Some problems that can be encountered are:

- training process can be quite lengthy
- over-training can result in memorization, resulting in a poor job of generalization
- Possibility of existence of local minimum for networks with more than 3 layers

The ANN used in this paper consists of input layer (3 inputs), hidden (16 neurons) and output layers (one outputs) as shown in tables 2 and 3.

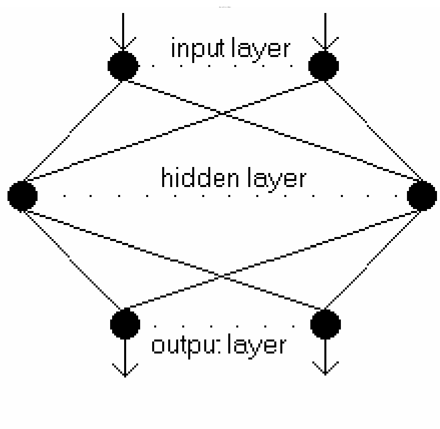

Figure 2: ANN Architecture

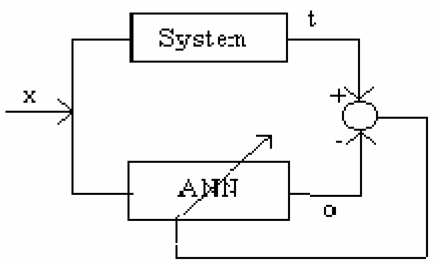

Figure 3: ANN Training Process

Table 1 Input Patterns For Training

Pf	P(Gw)	Q(Gvar)
1	0.6375	0.6375
0.75	0.6	0.45
0.5	0.75	0.375
0.25	0.75	0.1875
-0.25	0.725	0.18125

Table 2 Output Patterns For Training

Vcr(Mv)	C(Mvr)
0.1229	120
0.14	140
0.1389	150
0.1569	145
0.2038	140

Table 3: MSE Error Between ANN Outputs and Actual Ones

P_f	P (MW)	Q_L (MVar)	Mse (in Vcr)	Mse (in Qc)
0.76	600	456	0.0143	0.0157
0.98	625	612.5	0.01940	0.0019

4. Simulation And Results

Figure 4 shows the representation of the proposed system by Matlab-Power System Toolbox.
AC load flow was done using Matlab-Power System Toolbox.

4.1 Off-Line Data Collection for ANN

From the mentioned P-V curve method the training data for ANN are generated. For each power factor both the critical voltage and the shunt capacitor bank vlues are calculated. Table 1 and 2 show the training input and output data

4.2 Training Step

The offline data input-output pairs of critical voltage and the shunt capacitor bank vlues are presented to the network repeatedly. With each presentation (called also epoch), an input pattern is passed forward through each layer of the network. As illustrated in Figure 2, the output value from each neuron is equal to the sum of the weighted inputs. Each input vector is passed forward through the network and an output vector is calculated. During training, the network output is compared to the actual output (Figure 3), an error term is created. This error is fed backward through the network, from the output layer, through the hidden layer, and back to the input layer. The interconnection weights between each layer are adjusted based on the computed error and a learning rate variable. The process of presenting input data, passing it forward through the network and backpropagating the error, is repeated for each input. The training sets are presented to the network many times until the average error between the actual and ANN output is less than a predetermined error which equals to 10^{-9}. Once trained, ANN was found to predict extremely fast and exactly the critical voltage and the shunt capacitor bank values for the trained cases.

4.3Testing Step

Once trained, ANN was tested for unseen cases as shown in tables 3, the Mean Squared Errors (MSE) between the actual and calculated ones for both V_{cr} and Q_C (the values of the shunt capacitor banks to be inserted at the load buses) are very small.

5. Conclusion

ANNs have been developed and applied for voltage collapse prediction. Results obtaining show that ANNs are useful for voltage collapse prediction because they are characterized by having suitable basic properties:

- Can be trained with off-line data.
- Gives the dispature on line corrective action (by inserting parallel capacitors) to prevent the voltage collapse.
- Respond faster than the conventional techniques because there is no much calculations involved.

The above advantageous of the new technique will make the power system more reliable, more secure, and more stable.

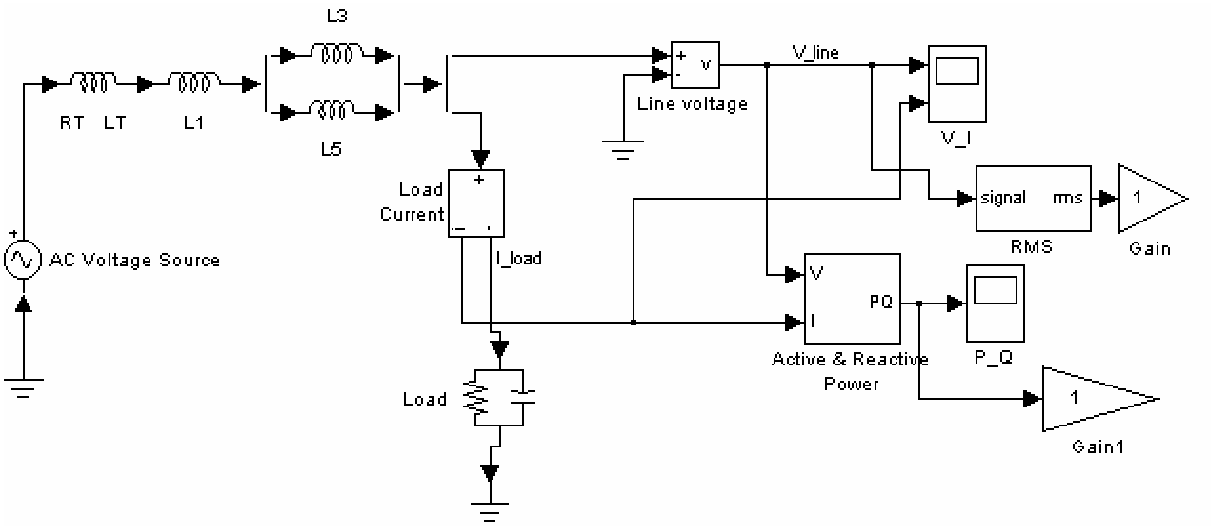

Figure 4:Representation of the Proposed System by Matlab-Power System Toolbox

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