POWER SYSTEM TRANSIENT STABILITY MARGIN ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper presents a methodology for estimating the normalized transient stability margin by using the multilayered perceptron (MLP) neural network. The complex relationship between the input variables and output variables is established by using the neural networks. The nonlinear mapping relation between the normalized transient stability margin and the operating conditions of the power system is established by using the MLP neural network. To obtain the training set of the neural network the potential energy boundary surface (PEBS) method along with time domain simulation method is used. The proposed method is applied on IEEE 9 bus system and the results shows that the proposed method provides fast and accurate tool to assess online transient stability.

KEYWORDS

Power system stability, transient energy function, potential energy boundary surface (PEBS), neural networks, ETAP software.

1. INTRODUCTION

Present power systems are large interconnected networks which span over entire countries and even continents are linking with the generators and loads. The main requirement for the reliable operation of the power system is that the system should be stable when a fault occurs on the system. A system is generally said to be transiently stable, if all the synchronous machines of the system remain in synchronism during the short period following a large disturbance. The transient stability is a fast phenomenon and usually occurring within 1 sec for a generator close to the cause of disturbance. The time domain simulation method is the most commonly used method to solve the set of nonlinear equations describing the system dynamic equations, in order to determine the transient stability [1]. From the inspection of the solution, conclusion can be drawn whether the system is stable or unstable.

In the actual operation of a power system the loading conditions and the parameters of the system are quite different from those assumed at the initial planning stage. Therefore for the better assessment of transient stability the system operator should simulate the contingencies in advance, access the results and take preventive control action if required. The time-domain simulation method is the most accurate method for accessing the transient stability but the disadvantage of this method is that, it will take more time and does not provide information about the transient energy margin. The equal area criterion can be applied for assessing the transient stability but this method has some modelling limitations. The transient energy function method can also be applied but this method has also some modelling limitations. Both the equal area

criterion and transient energy methods need a lot of computations to determine the transient stability [2, 3]. Since the transient stability is a fast phenomenon, so better methods should be used to assess the transient stability which provide fast and accurate results.

Neural networks can be used to access the transient stability of the large power systems. The main advantage of the neural networks is that it will learn complex relationships and their modular structure which allows parallel processing. The main objective of the present investigation is to propose a MLP neural network based approach for online transient stability analysis through estimation of a normalized transient stability margin (ΔV_n) [4]. In this paper we have taken ΔV_n is a function of only pre-fault system operating point, which can be adequately characterized by a proper set of readily measurable operating conditions in the pre-fault situations. The potential energy boundary surface method along with time domain simulation method is used to obtain critical energy for the particular disturbance under investigation.

2. MULTI-LAYERED PERCEPTRON NEURAL NETWORK

Neural networks are inspired by the Human brain. A brain is a massively parallel distributed system made up of highly interconnected neural computing elements called as neurons, which have the ability to learn and thereby acquire knowledge and make it available for use. The neurons are also called as neurodes, processing elements or nodes. The complex relationship between the input variables and output variables is established by using the neural networks. A multilayered feed forward neural network is also known as multi layer perceptron. This neural network consists of an input layer, an output layer and one or more hidden layers. Generally one hidden layer is sufficient to establish complex relationship between the input and output. The number of neurons in the input layer and output layer depends on the specific problem but the number of neurons in the hidden layers is arbitrary and is usually decided by trial and error method [5, 6].

Fig.1. A multilayered perceptron with one hidden layer

The neural network is used to adjust the weights and biases of the network in order to reduce the error between the desired output and obtained output. This process of adjusting the weights and biases is known as training. Different algorithms are present to train the neural network. In this paper we have used Trainlm as the training function [7]. Trainlm is the best algorithm compared to other algorithms present up to so far. To obtain the training data the Potential Energy Boundary Surface (PEBS) method along with time domain simulation method is used.

3. NORMALIZED TRANSIENT ENERGY MARGIN

Consider a power system composed of n synchronous generators. The motion of the i th machine of an n -machine system reduced to generator internal nodes, using classical machine model representation is described in the Centre of Inertia (COI) formulation [8, 9] by

$$\frac{d\theta_i}{dt} = \tilde{\omega}_i \quad (1)$$

$$M_i \frac{d\tilde{\omega}_i}{dt} = P_{mi} - P_{ei} - \frac{M_i}{M_T} P_{COI} = f_i(\theta) \quad i=1, 2 \dots n \quad (2)$$

Where,

$$P_{ei} = E_i^2 G_{ii} + \sum_{j=1 \neq i}^n (C_{ij} \sin \theta_{ij} + D_{ij} \cos \theta_{ij}) \quad (3)$$

$$P_{COI} = \sum_{i=1}^n (P_{mi} - P_{ei}) \quad (4)$$

Where,

$$C_{ij} = E_i E_j B_{ij}, D_{ij} = E_i E_j G_{ij}, Y_{ij} = G_{ij} + jB_{ij} \text{ and } M_T = \sum_{i=1}^n M_i \quad (5)$$

Where θ_i is the rotor angle, $\tilde{\omega}_i$ is the rotor speed, M_i is inertia constant, P_{mi} is the input mechanical power, P_{ei} is the output electrical power, E_i is the generator internal voltage for machine i , Y is the reduced admittance matrix and Y_{ij} is the ij th element of the reduced admittance matrix. G_{ij} and B_{ij} are conductance and susceptance elements of the reduced admittance matrix.

The energy function for the post-fault system is constructed as

$$\begin{aligned} V(\theta, \omega) &= \frac{1}{2} \sum_{i=1}^n M_i \omega_i^2 - \sum_{i=1}^n \int_{\theta_i^s}^{\theta_i} f_i(\theta) d\theta_i \\ &= V_{KE}(\tilde{\omega}) + V_{PE}(\theta) \cong V_{TOT} \end{aligned} \quad (6)$$

Where θ_i and $\tilde{\omega}_i$ are the variables from the faulted trajectory. In the absence of the transfer conductance terms G_{ij} , the expression for $V_{PE}(\theta)$ can be expressed analytically in a closed form, otherwise the G_{ij} terms contribute a path dependent term as follows

$$V_{PE}(\theta) = \sum_{i=1}^n P_i(\theta_i - \theta_i^s) - \sum_{i=1}^{n-1} \sum_{j=i+1}^n \left[C_{ij} (\cos \theta_{ij} - \cos \theta_{ij}^s) - \int_{\theta_i^s + \theta_j^s}^{\theta_i + \theta_j} D_{ij} \cos \theta_{ij} d(\theta_i + \theta_j) \right] \quad (7)$$

Where,

$$P_i = P_{mi} - |E_i|^2 G_{ij}$$

In computing Eq. (7) θ_i is obtained from the faulted trajectory and θ_i^s is obtained from the post-fault stable equilibrium point. The third term of Eq. (7) is path dependent. By assuming a straight line path of integration, the third term of Eq. (7) is approximated analytically as

$$\int_{\theta_i^s + \theta_j^s}^{\theta_i + \theta_j} D_{ij} \cos \theta_{ij} d(\theta_i + \theta_j) \cong D_{ij} \frac{(\theta_i - \theta_i^s) + (\theta_j - \theta_j^s)}{(\theta_i - \theta_i^s) - (\theta_j - \theta_j^s)} (\sin \theta_{ij} - \sin \theta_{ij}^s) \quad (8)$$

After the removal of a disturbance, if the power system is stable then a certain amount of kinetic energy is not absorbed. This indicates that not all the transient kinetic energy, created by the disturbance, contributes to the instability of the system. Some of the kinetic energy created by the disturbance is responsible for the inter-machine motion between the generators [10, 11], and does not contribute to the separation of the severely distributed generators from the rest of the system. Therefore by using the transient energy function method in order to assess the accurate transient stability, the amount of kinetic energy which is not contributing to the instability of the system should be subtracted from the energy that needs to be absorbed by the system for stability to be maintained. If the inertias of the system are finite, the disturbance splits the generators of the system into two groups: the critical machines and the rest of the generators [12, 13]. Their angular speeds and inertial centres have inertia constants $\tilde{\omega}_{cr}$, M_{cr} , $\tilde{\omega}_{sys}$, M_{sys} respectively. These parameters are obtained as follows

$$M_{cr} = \sum_{i \in cr} M_i, \quad M_{sys} = \sum_{i \in sys} M_i \quad (9)$$

$$\tilde{\omega}_{cr} = \frac{\sum_{i \in cr} M_i \tilde{\omega}_i}{M_{cr}}, \quad \tilde{\omega}_{sys} = \frac{\sum_{i \in sys} M_i \tilde{\omega}_i}{M_{sys}} \quad (10)$$

In the Eq. (9) and Eq. (10) the subscript “cr” denotes the critical machines group and “sys” denotes the rest of the machines in the system. The kinetic energy which is responsible for the separation of the two groups [14, 15, 16] is the same as that of an equivalent one-machine-infinite-bus system having inertia constant M_{eq} and angular velocity $\tilde{\omega}_{eq}$ given by

$$M_{eq} = \frac{M_{cr} M_{sys}}{M_{cr} + M_{sys}} \quad (11)$$

$$\tilde{\omega}_{eq} = (\tilde{\omega}_{cr} - \tilde{\omega}_{sys}) \quad (12)$$

And the corresponding kinetic energy is given by

$$V_{KEcorr} = \frac{1}{2} M_{eq} \tilde{\omega}_{eq}^2 \quad (13)$$

Therefore the kinetic energy in Eq. (6) is replaced by Eq. (13).

By computing the two values of the transient energies the transient stability can be assessed.

- 1) The value of the transient energy is normally determined at fault clearing time, V_{cl} and
- 2) The critical value of the transient energy function V_{cr} which is evaluated at the Controlling Unstable Equilibrium Point (CUEP) for the particular disturbance under investigation. If $V_{cl} < V_{cr}$ then the system is stable. In this paper we have used Potential Energy Boundary Surface (PEBS) method along with Time Domain Simulation (TDS) method to calculate the V_{cr} . In other way the transient stability can be assessed by computing the transient stability margin ΔV [17, 18] given by

$$\Delta V = V_{cr} - V_{cl} \quad (14)$$

If ΔV is greater than zero the system is stable, and if ΔV is less than zero the system is unstable. For the purpose of training the neural networks we have define a normalized transient energy margin ΔV_n [19]. This normalized transient stability margin is calculated differently for stable and unstable cases as

$$\Delta V_n = \begin{cases} \frac{V_{cr} - V_{cl}}{V_{cr}} & \text{If system is stable } (t_{cr} > t_{cl}) \\ \frac{V_{cr} - V_{cl}}{V_{cl}} & \text{If system is unstable } (t_{cr} < t_{cl}) \end{cases} \quad (15)$$

From the above, we can easily shown that the ΔV_n lies between -1 and +1.

If $\Delta V_n > 0$, the system is stable, and if $\Delta V_n < 0$, the system is unstable. This normalized transient energy margin represents a quantitative measure of degree of stability or instability of the system. In this paper we have used the following procedure [20, 21] to obtain the normalized transient energy margin

- (1) Find the post-fault stable equilibrium point (θ^s) by solving

$$f_i(\theta) = 0 \quad i=1, 2 \dots n$$
- (2) Integrate Eq. (1) and Eq. (2) to obtain the faulted trajectory.
- (3) Monitor Eq. (7) to obtain $V_{PE}(\theta)$ at each time step. The parameters in $f(\theta)$ and $V_{PE}(\theta)$ pertain to post fault system.
- (4) Continue steps 2 and 3 until the transient potential energy reaches a maximum along the faulted trajectory. Denote this maximum value by V_{cr}' . This is a good estimate for actual V_{cr} for that fault.
- (5) From the faulted trajectory find the time instant t_{cr}' at which the transient energy V reaches V_{cr}' . The t_{cr}' is viewed as an estimate of actual t_{cr} .
- (6) Find actual t_{cr} by using t_{cr}' as an initial guess in the time-domain simulation technique accompanied by trial and error method.
- (7) Integrate the faulted system dynamic equations until time instant, $t=t_{cr}$. Find the value of system potential energy at this time instant. Also find the system corrected kinetic energy using Eq. (13). Then obtain the system critical energy V_{cr} by adding the system potential and corrected kinetic energies.

- (8) Integrate faulted system dynamic equations until time instant $t=t_{cl}$. Find the value of system potential energy at this time instant. Also find the system corrected kinetic energy using Eq. (13). Then obtain the system total energy at fault clearing time V_{cl} , by adding the system potential and corrected kinetic energies.
- (9) Compute the system normalized transient stability margin ΔV_n using Eq. (15).

4. THE PROPOSED METHODOLOGY

The IEEE 3 machine, 9 bus system is taken as the test system. The IEEE 9 bus system consists of 3 load buses, 3 generators and 6 lines.

Fig.2. Single line diagram of IEEE 9 bus system

Assume that at time $t=0$, a three phase fault occurs on line 3 near bus 7. For this system critical clearing time is found to be 0.216 sec in the base case loading conditions. Assume that in the first case the fault is eliminated by removing the transmission line connected between the buses 5 and 7 at 0.1 sec the rotor angle differences of the generators are as shown in the Fig.3.

Fig.3. Rotor angle differences of generators with Gen-1 as reference (stable case)

For this case the normalized energy margin is found to be 0.8516 hence the system is stable. Also by observing the rotor angle differences of generators in Fig.3 we can say that the system is stable. Assume that in the second case the fault is eliminated by removing the transmission line connected between the buses 5 and 7 at 0.5 sec the rotor angle differences of the generators are as shown in the Fig.4.

Fig.4. Rotor angle differences of generators with Gen-1 as reference (Unstable case)

For this case the normalized energy margin is found to be -0.6460, hence the system is unstable. Also by observing the rotor angle differences of the generators in Fig.4 we can say that the system is unstable. In both the cases we have not considered any critical machines.

5. SIMULATION RESULTS

The proposed multilayer perceptron neural network (MLP) based method for online transient stability monitoring has been applied to IEEE 9 bus system.

Fig. 5.Simulation of IEEE 9 bus system in ETAP software

Assume that at time $t=0$, a three phase fault occurs on line 3 near bus 7. For this particular fault we will use the ANN for assessing the normalized transient energy margin. The input for the ANN is

- Active powers of all generator connected buses (P_{g1} , P_{g2} , and P_{g3})
- Voltage magnitudes of all generator connected buses (V_{g1} , V_{g2} and V_{g3})
- Active load powers of all 3 loads acting on different buses (P_{l1} , P_{l2} and P_{l3})
- Reactive load powers of all 3 loads acting on different buses (Q_{l1} , Q_{l2} and Q_{l3}).

Thus the MLP neural network inputs are the above mentioned $(3+3+3+3) = 12$ independent operating conditions whereas its output is ΔV_n . We have taken two hidden layers with 20 and 10 hidden neurons in first and second hidden layers respectively. The ANN is trained by using Trainlm as the training function. It is to be noted that once the training of the MLP neural network is completed, the ΔV_n can be quickly computed. We have taken 60 random data patterns from which 80% are used for training 10% are used for testing and 10% are used for validation. The fault clearing time is taken as 0.101sec. The output of the ANN for the 10 patterns is shown in Table 1. We can see from the results that the normalized energy obtained by ANN is close to the actual value.

Table.1 Comparison of actual and estimated ΔV_n

P_{g1}	P_{g2}	P_{g3}	V_{g1}	V_{g2}	V_{g3}	P_{11}	P_{12}	P_{13}	Q_{11}	Q_{12}	Q_{13}	ΔV_n	ΔV_n By ANN
74.6	156	85	1	1	1	121.3	87.3	106.8	48.5	29.1	34	0.8773	0.8773
67.6	163	85	1	1	1	121.3	87.3	106.8	48.5	29.1	34	0.8665	0.8666
61.6	165	89	1	1	1	121.3	87.3	106.8	48.5	29.1	34	0.7956	0.7956
61.6	165	85	0.969	1	1	119.8	86.2	105.4	47.9	28.7	33.6	0.8751	0.8749
71.2	161	89	1	1	1.029	123.5	88.9	108.7	49.4	29.6	34.6	0.9003	0.9004
64.8	165	85	1	1	1	121	87.1	106.5	67.8	19.4	33.9	0.8656	0.8660
72	165	85	1.048	1	1	123.8	89.1	108.9	49.5	29.7	34.7	0.7789	0.7789
36.5	165	85	1	1	1	121.3	58.2	106.8	48.5	29.1	34	0.8400	0.8399
7.4	165	85	1	1	1	121.4	29.1	106.8	48.5	29.1	34	0.7831	0.7831
62.7	165	85	1	1	0.985	120.2	86.6	105.8	48.1	28.8	33.7	0.8282	0.8281

6. CONCLUSIONS

Fast transient stability assessment (TSA) is greatly important in the actual operation of power system. In this paper we have presented a multi-layered-perceptron (MLP) neural network based approach for online TSA through estimation of a normalized transient stability margin (ΔV_n) for a particular contingency under different operating conditions. Simulation results on the IEEE 9 bus system demonstrated that the proposed method was capable of estimating ΔV_n with a good degree of accuracy. From the results we can say that the proposed approach is well suitable for online normalized transient stability margin estimation.

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