

ANN BASED HVDC CONTROLLERS FOR POWER OSCILLATION DAMPING IN MULTI MACHINE POWER SYSTEM USING EXTREME LEARNING MACHINE ALGORITHM

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Abstract

This paper discusses the artificial intelligence-based controllers for HVDC in multi machine AC-DC power system. In the last decade Researchers have applied AI based HVDC controllers to improve the stability limit in large inter connected power system. Artificial neural network-based controllers are popular among other controllers falls in this category. The performance of these controllers majorly depends on the method of training the neural network. Even though back propagation algorithm finds to be suitable for many applications, it also suffers from the draw backs like slow convergence, local minima and longtime taking in convergence. These disadvantages are overcome using Extreme learning machine algorithm trained neural networks. The effectiveness of the proposed training algorithm is tested on IEEE 9-Bus test power system using MATLAB/SIMULINK under different fault conditions.

KEYWORDS: Transient stability, HVDC controllers, ELM algorithm, Angle, Stability, Power oscillation damping.

Introduction:

One of the problems in the operation of interconnected power system is maintenance of system stability. As power systems have evolved through continuing growth in interconnections, use of new technologies and controls, and the increased operation in highly stressed conditions and different forms of system instability have emerged [1]. Power systems are subjected to a wide range of disturbances, small and large. Small disturbances in the form of load changes occur continually; the system must be able to adjust to the changing conditions and operate satisfactorily. Effective power controlling capabilities of HVDC links play major role in transient stability improvement in multi machine AC-DC power systems. The performance of these controllers can be enhanced by the use of ANN based techniques. However, the performance of these controllers greatly depends on the method of training the ANN. Back Propagation algorithm is popularly used to train the ANN. However, over training data in training BP

algorithm results in local minima and slow convergence. To address the disadvantages of BP algorithm, Extreme Learning Machine algorithm is used to train the neural network. The proposed ELM algorithm has only one hidden layer. The weights of the neurons between input layer and hidden layer are randomly chosen and weights of the neurons between hidden layer and output layer are analytically calculated. Performance of the proposed algorithm is tested on IEEE 3-machine, 9-bus test power system.

Modelling of AC-DC system for Transient stability studies

Load flow studies are carried on the test system and the results serves as initial conditions for fault studies. Eliminated variable method is used to estimate the voltages and initial power flows in the system. The power flow variables at the DC link buses are considered as voltage dependent loads[2]. The D.C link equations are solved numerically and eliminated from the power flow methods[3].

a) D.C system model

The steady state equations of d.c link are

$$\begin{aligned}
 V_{dr} &= \frac{\sqrt[3]{2}}{\pi} a_r V_{tr} \cos \alpha_r - \frac{3}{\pi} X_c I_d \dots\dots\dots 1 \\
 V_{di} &= \frac{\sqrt[3]{2}}{\pi} a_i V_{ti} \cos \gamma_i - \frac{3}{\pi} X_c I_d \dots\dots\dots 2 \\
 V_{dr} &= V_{di} + r_d I_d \dots\dots\dots 3 \\
 P_{dr} &= V_{dr} I_d \dots\dots\dots 4 \\
 P_{di} &= V_{di} I_d \dots\dots\dots 5 \\
 S_{dr} &= k \frac{\sqrt[3]{2}}{\pi} a_r V_{tr} I_d \dots\dots\dots 6 \\
 S_{di} &= k \frac{\sqrt[3]{2}}{\pi} a_i V_{ti} I_d \dots\dots\dots 7 \\
 Q_{dr} &= \sqrt{S_{dr}^2 - P_{dr}^2} \dots\dots\dots 8 \\
 Q_{di} &= \sqrt{S_{di}^2 - P_{di}^2} \dots\dots\dots 9
 \end{aligned}$$

b) Eliminated variable method

The real and reactive powers at either side of the converter are represented as function of converter bus voltages. Power flow equations and D.C equations are solved one after other that is by sequential method. This method eliminates the complexity of finding the derivatives of real and reactive power.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} H & N \\ J & L \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta V/V \end{bmatrix} \dots\dots\dots 10$$

$$N'_{tr, tr} = V_{tr} \frac{\partial P_{tr}^{ac}}{\partial V_{tr}} + V_{tr} \frac{\partial P_{dr} V_{tr}, V_{ti}}{\partial V_{tr}} \dots\dots\dots 11$$

$$N'_{tr, ti} = V_{ti} \frac{\partial P_{tr}^{ac}}{\partial V_{ti}} + V_{ti} \frac{\partial P_{dr} V_{tr}, V_{ti}}{\partial V_{ti}} \dots\dots\dots 12$$

$$N'_{ti, tr} = V_{tr} \frac{\partial P_{ti}^{ac}}{\partial V_{tr}} - V_{tr} \frac{\partial P_{dr} V_{tr}, V_{ti}}{\partial V_{tr}} \dots\dots\dots 13$$

$$N'_{ti}, t_i = V_{ti} \frac{\partial P_{ti}^{ac}}{\partial V_{ti}} - V_{ti} \frac{\partial P_{di} V_{tr}, V_{ti}}{\partial V_{ti}} \dots\dots\dots 14$$

Hence the number of equations remains same.

Synchronous Machine Representation

Synchronous generator is modeled by using two variables, terminal voltage and leakage flux. The assumptions made in this model are constant flux linkages and saliency in poles is neglected.

$$\frac{d\delta}{dt} = \omega - 2\pi f \dots\dots\dots 15$$

$$\frac{d^2\delta}{dt^2} = \frac{d\omega}{dt} = \frac{\pi f}{H} P_m - P_e \dots\dots\dots 16$$

Load representation

Constant admittance form of load representation is suitable for transient stability studies. The equation of the load is given by

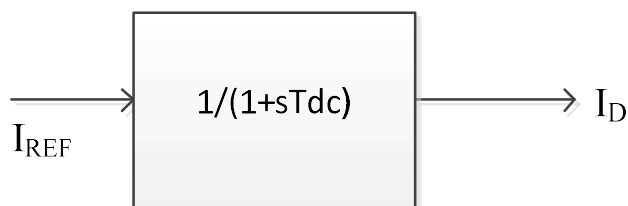
$$Y_{po} = \frac{I_{po}}{E_p} \dots\dots\dots 17$$

Where

$$I_{po} = \frac{P_{lp} - jQ_{lp}}{E_p^*}$$

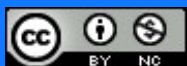
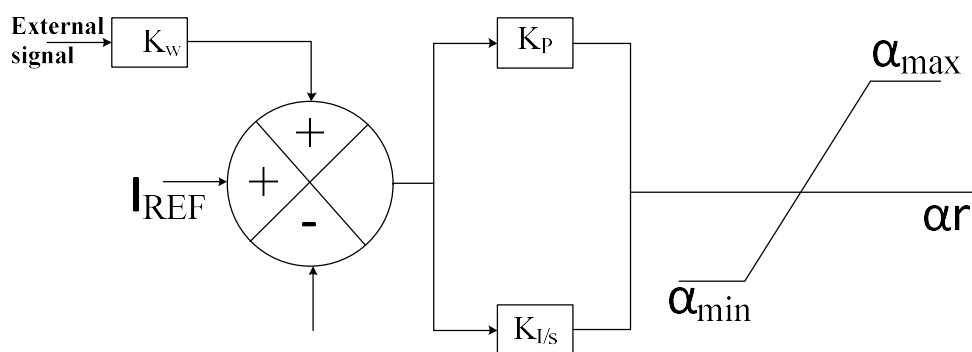
HVDC Representation

The D.C line in the system is modeled in the form of Transfer function as given in the fig(1)



Transfer function model of HVDC link Fig (1)

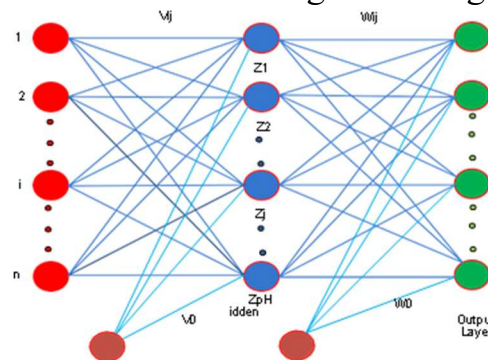
The control structure to damp power oscillations in d.c link is shown in fig(2). Conventional PID controller is replaced by the ANN controller trained initially by back propagation algorithm and then by ELM algorithm as explained in the next sessions.



Fig(2): HVDC control scheme

BackPropagationAlgorithm

The performance of the multi-layer ANN mainly depends on the training data and training method. BackPropagationalgorithm(BP) is an efficient[8] training algorithm which uses extended descent gradient method to adjust the weights of the neurons. In BP algorithm weights are calculated in every stage and adjusted in accordance with the activation function of the problem. output layer and again weighted sum or activation values will be calculated at each unit in the output layer which are processed through activation function to find the output. The output values are compared with the target values and square of error is calculated to adjust the weights further. To minimize the error first weights connects immediate layers are modified. The architecture of the algorithm is given in fig(3).



Figure(3) Architectures of general and proposed MNN

The input layer has 'n' neurons, hidden layer has 'p' neurons and output layer has 'm' neurons. The factor W_{jk} is the weight of the neuron between j^{th} and k^{th} layer. Initially weights are taken randomly. The outputs of hidden layer neurons will be the inputs to the neurons in the output layer. The weighted sum and the output at all the neurons in the output layer can be calculated as given in Equations.

The fitness function for each neuron is estimated then output is compared with the target output and squared error is calculated. The weights are modified till the error is minimized. The weights are modified by using the following equations

$$W_{jk}(\text{new}) = W_{jk}(\text{old}) + \Delta W_{jk},$$

$$W_{ok}(\text{new}) = W_{ok}(\text{old}) + \Delta W_{ok}$$

$$\text{Where } \Delta W_{jk} = \eta * \frac{\partial E}{\partial W_{jk}} = \eta * \delta_k * Z_j$$

$$\Delta W_{ok} = \eta * \frac{\partial E}{\partial W_{ok}} = \eta * \delta_k$$

The weights of the neurons between input and hidden layer are modified as follows

$$V_{ij}(\text{new}) = V_{ij}(\text{old}) + \Delta V_{ij}$$

$$V_{oi}(\text{new}) = V_{oi}(\text{old}) + \Delta V_{oi}$$

Where

$$\Delta V_{ij} = \eta * \delta_j * X_i$$

$$\Delta V_{oi} = \alpha * \delta_i \quad (4.11)$$

Algorithm

Step1: Randomly choose the weights of all neurons

Step2: Speed change of the generators is input to BP algorithm.

Step3: Estimate the outputs of the hidden and output layers. In this problem the change in the line power is the output.

Step4: Estimate the squared error which is to be minimized for better output.

Step5: Update the weights between output and hidden, hidden, and input layers in the backward process.

Step6: Repeat the procedure till the squared error is below 0.001.

However, the algorithm suffers from the drawbacks like slow convergence, local minima and long time taking.

Extreme Learning Machine Algorithm:

The drawbacks in BP algorithm can be addressed by Extreme Learning Machine algorithm. This algorithm is effective in training single hidden layer neural networks. The key point in this algorithm is that the weights between input and hidden layer are taken randomly and the weights between output and hidden layers are calculated mathematically. The general form of ELM network is as shown in fig(4)

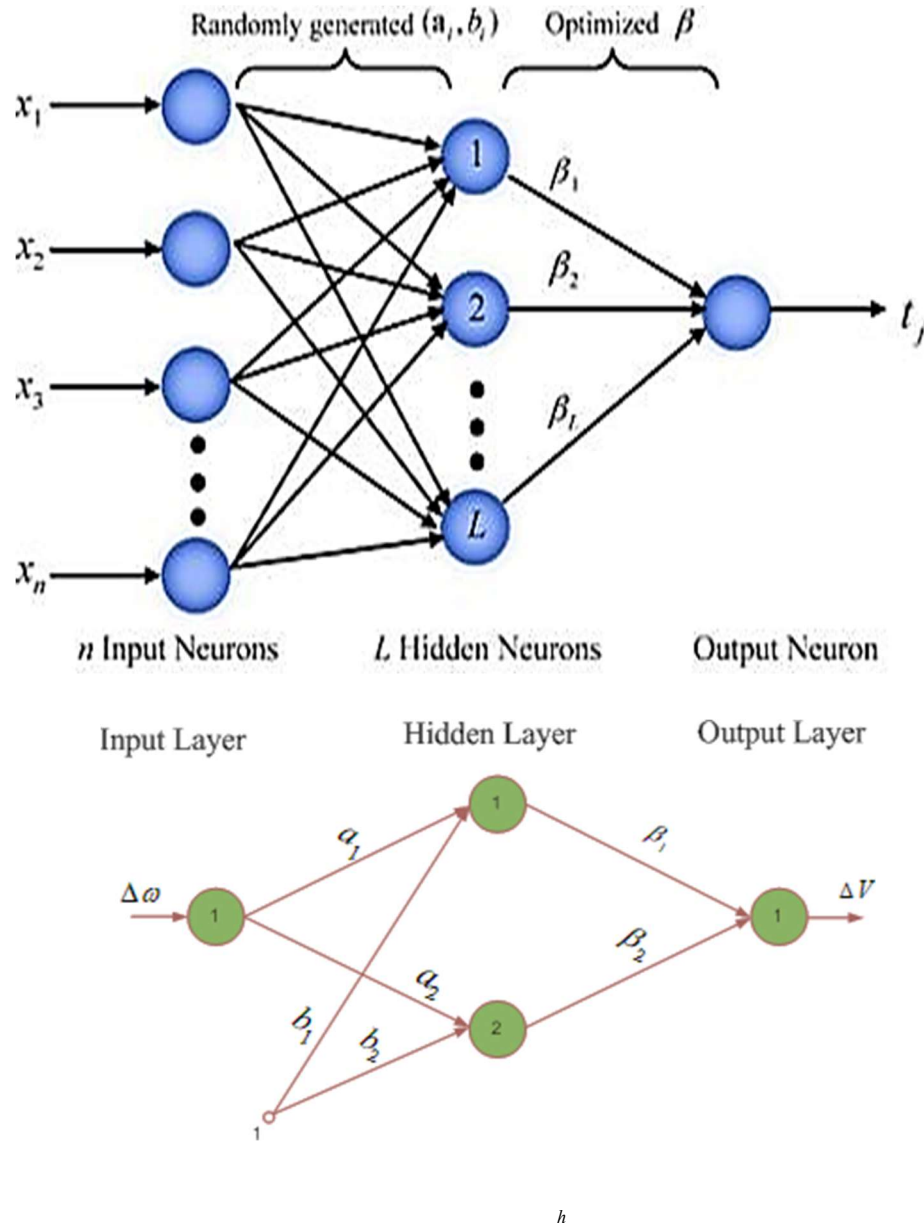


Figure (4) Layout of general and proposed single hidden layer ELM network

x_1, x_2, \dots, x_n are the inputs (speed deviations) applied at the input layer to minimize the power changes in the line, that is the activation function $(x_i \cdot a_k + b_i)$ at each particle in the hidden layer will be

$$g(x_i \cdot a_k + b_i) \cdot t_j$$

calculated using randomly generated weights a_k and b_i . Using the variables (β_j) and the target values t_j , the weights between hidden and output layer will be calculated as

$$G \beta = T$$

Where, G is matrix of outputs of hidden layer and Y is output matrix of ELM

$$\begin{bmatrix} g(a_1 \cdot x_1 + b_1) & \circ & \circ & g(a_m \cdot x_1 + b_m) \\ \circ & \circ & \circ & \circ \\ \circ & \circ & \circ & \circ \\ g(a_1 \cdot x_n + b_1) & & & g(a_m \cdot x_n + b_m) \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ 0 \\ 0 \\ \beta_m^T \end{bmatrix} \quad T = \begin{bmatrix} t_1^T \\ 0 \\ 0 \\ t_n^T \end{bmatrix}$$

For randomly assigned input weights and biases, the output weight matrix elements are calculated as:

$$\beta = G^+ T$$

Where G^+ is the Moore–Penrose inverse of G matrix, which is evaluated from Singular value decomposition.

Methodology:

Step1: The change of speed of the machines is given as input to the network

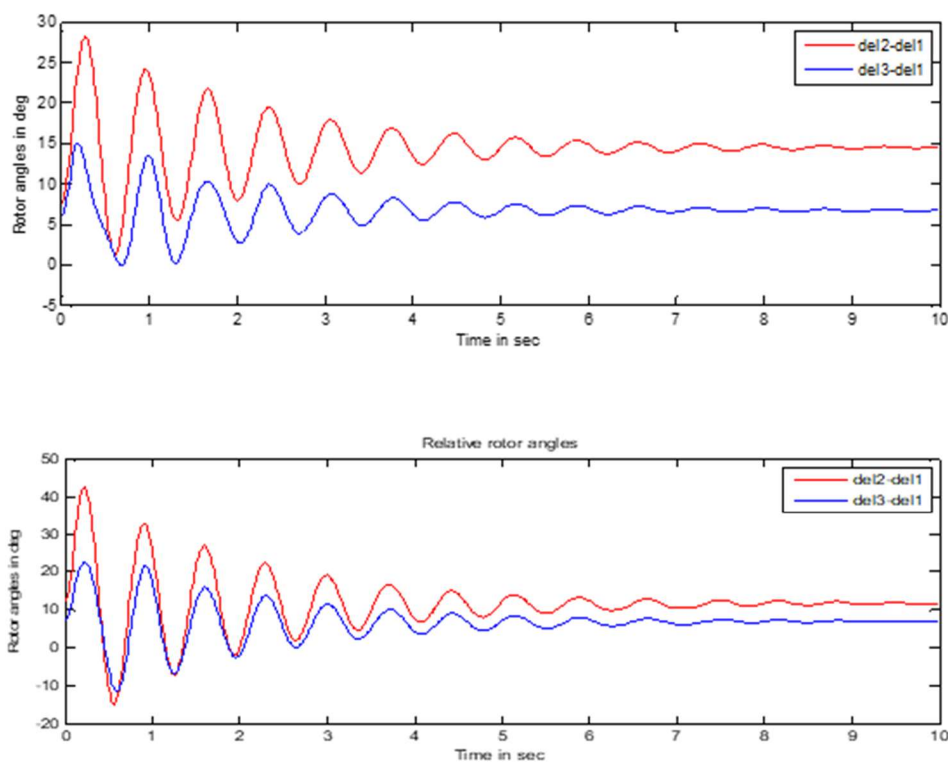
Step2: Randomly choose the input weights and bias values.

Step3: The output weights are estimated using the mathematical equations.

Step4: With the calculated output weights, the output i.e. change in power will be estimated

Results And Discussion

The effectiveness of the proposed algorithm is applied to WSSC 3-machine,9-bus power system. Figure(2) shows the single line diagram of the test power system. The transmission line connected between bus 4 and 5 is converted as HVDC line for power control under abnormal conditions. A three phase fault is applied at bus 9 for a duration of 6 cycles and the relative rotor angles w_{2-1} and w_{3-1} are plotted as shown in fig() and fig() respectively. Initially the ANN network is trained using BP algorithm, a three-phase fault is assumed at bus 9 for a duration of 6 cycles. The relative rotor angles of second and third generator are plotted w.r.t to first generator as shown in fig(). The effectiveness of the proposed algorithm is examined with the similar fault conditions as said above. The relative rotor angles are as shown in fig(). It is observed that the first swing is reduced for all generators which emphasis the transient stability improvement. Reduced speed deviations of the generators results less power swings in the faulted line. The settling time of the generators is also reduced significantly with ELM trained ANN network.



Conclusions

This paper demonstrates the application of ANN based HVDC controllers to multi-machine power system. ANN based controllers gives enhanced Performance with efficient training methods. Back propagation algorithm is initially used to train the ANN. The disadvantages of BP are overcome with ELM trained ANN networks. Both the algorithms are applied on the same test power system with similar fault conditions. The results given emphasis the better performance of the proposed training algorithm. Improvement in transient stability and reduced power oscillation damping are observed.

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