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Neuro-controllers for Synchronous Generators

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Abstract: Automatic voltage regulators (AVRs) are controllers used to maintain constant voltage at the generator terminals. Artificial Neural Networks (ANNs) are nonlinear maps that have the potential to make the realisation of practical nonlinear controllers possible. This paper is concerned with the development of a Feedforward Multilayer Perceptron (MLP) Neural Networks and its use as an Automatic Voltage Regulator (AVR) with Power System Stabiliser (PSS). The performance of the MLP-AVR is compared with that of a conventional AVR with PSS. The MLP-AVR shows good performance compared to that of conventional AVR with PSS.

Keywords: Neural networks, automatic voltage regulator, power system stabiliser, excitation system, stability

1. INTRODUCTION

The electric grid is highly dynamic and nonlinear. Its complexity continues to rise further due to the integration of intermittent renewable energy power sources and intensification of demand for capacity. Control of the grid must be accurate enough to ensure consistent level of power quality and robust enough to fortify its stability. The ability for synchronous generators to remain in step determines the stability of the grid. Excitation systems which comprise of an automatic voltage regulator (AVR) and power system stabilizer (PSS) are used to keep generators in synchronism (Glover *et al*, 2008), (Kundur, 1994), (Rogers, 2000). These control systems are designed using linear control techniques and only perform well around the nominal operating points (Kundur, 1994), (Rogers, 2000). However power systems are nonlinear and highly complex; intuition would suggest that nonlinear techniques would better serve the purposes of ensuring efficient control and stability. Nonlinear control techniques have been investigated for a number of years, but they have produced very little in the form practical methods of synthesis as well as procedures for practical implementation (Ogata, 2008).

Artificial Neural Networks (ANNs) are adaptive nonlinear maps that accept inputs from one finite dimensional space and produce outputs in another finite space. This inherent nonlinearity makes them very useful tools in complex, uncertain and dynamic environments (Engelbrecht, 2007), (Narendra, 1996). The power grid is a highly complex, uncertain and dynamic where ANNs have proved to be useful in providing effective control.

The Feedforward Multilayer Perceptron (MLP) is designed in this paper to replace the conventional AVR with PSS. The performance of the MLP is evaluated by subjecting the system (a single-machine infinite bus power system) to a 50ms three-phase-to-ground fault. Simulation results show that the MLP based excitation system has a superior performance when compared to a conventional AVR+PSS excitation system.

This paper is organized as follows:Section 2 presents a literature review. Section 3 presents the system model and design procedure for neuro-controlled excitation system. Section IV presents simulation results and section V gives conclusions and future work.

2. LITERATURE REVIEW

2.1 Overview of Artificial Neural Networks

The human brain is a continually evloving, fast acting and highly parallel computing unit. It has the ability to perform tasks such as inference, abstraction, deduction and classifcation almost instantly. It is able to perform these tasks many thousands of times faster than modern computers; where computers may not even be able to perform some of them.

Artificial Neural Networks (ANNs) are modeled after the the brain. They attempt to replicate the biological mechanisms that govern how it works (Engelbrecht, 2007), (Qiao, *et al*, 2007), (Venayagamoorthy, 2004). An ANN is a layered network of artificial neurons. An ANN may consist of an input layer, hidden layer and an output layer. The artificial neurons are modeled using a nonlinear function with convieniant mathmatical properties such as differntiability and limitted output range. Figure 1 illustrates the structure of an ANN.

Learning is facilitated in ANNs with the use of the back propagation supervised learning algorithm. There are two steps in the learning process, namely forward propagation and back propagation.

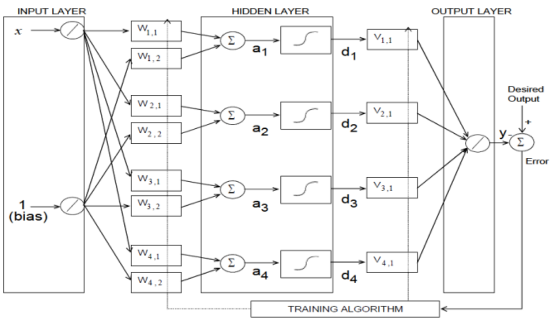

Fig 1. Multilayer Perceptron Artificial Neural Network Architecture (Venayagamoorthy, 2004)

Forward Propagation

The input signals received at the input layer are sent through to the hidden layer, aggregated and then squashed into an activation function. The hidden layer signal outputs are then sent to the output layer where they are again aggregated and then squashed into another activation function. For any pattern z_p this single pass through the network can be represented as follows:

$$o_{pj} = \psi_i (z_{o_{i,p}}) \tag{1}$$

$$o_{pj} = \psi_i (\sum_{j=1}^{j+1} w_{ji} \psi_{yj} (z_{yj,p})) \tag{2}$$

$$o_{pj} = \psi_i (\sum_{j=1}^{j+1} w_{ji} \psi_{yj} (\sum_{i=1}^{i+1} v_{ji} u_{i,p})) \tag{3}$$

Where $o_{i,p}$ is the output corresponding to a particular pattern, ψ_i is the activation function of a neuron, $z_{oi,p}$ is the aggregation of all the signals from the neurons in the final hidden layer, $w_{i,j}$ is the weight of a particular synaptic connection, $v_{j,i}$ is the weight corresponding to a particular input and $u_{i,p}$ is an input signal.

Backpropagation

The most widely used ANN training algorithm is the back propagation algorithm originally proposed in the 1970's (Venayagamoorthy, *et al*., 2003). Back propagation is also a stochastic search that aims at minimising an objective function. The most commonly used objective function is the derivative of the Mean Square Error (MSE) as given in the following equations:

$$E_p = 0.5(t_{pj} - o_{pj})^2 \tag{4}$$

$$-\frac{\partial E_p}{\partial o_{pj}} = t_{pj} - o_{pj} \tag{5}$$

$$-\frac{\partial E_p}{\partial o_{pj}} = \sum \partial_{p_i} W_{ij} \tag{6}$$

where E_p is the MSE, t_{pj} is the target output of the neuron j for pattern p and o_{pj} is the output produced by the ANNs.

When neuron j is in an output layer, equation (5) is used and when j is in a hidden layer equation (6) is used. The minimisation of the objective function is achieved through calculating the Jacobian matrix of the synaptic weights by using gradient decent algorithm to find update values for the weights. The update procedure is as follows:

$$w_{kij}(t+1) = w_{kij}(t) + \Delta w_{kij}(t) \tag{7}$$

$$\Delta w_{ji}(n) = \lambda . \delta_j . y_i(n) \tag{8}$$

$$\delta_j(n) = e_j(n) . \psi'_j(v_j(n)) \tag{9}$$

where w_{kij} is weight of neuron i in layer k of previous neuron j, λ is learning rate, δ is local gradient, e_j is output from error function and ψ'_j is derivation of activation function.

The main problem with the back propagation algorithm is its susceptibility to get stuck at local optima during stochastic search.

2.2 Artificial Neural Networks for Control

ANNs have been used in a wide range of applications such as modelling tools for regression, classification, and system approximation (Wolf and Shashua, 2005), (Starzyk, *et al*., 2005), (He and Starzyk, 2010), (Xiao, *et al*., 2010). They are also attractive as nonlinear controllers (Fukuda and Takanori, 1992), (Cong and Liang, 2009) due to their inherent nonlinearity, insensitivity to noise and robustness. Research in the use of ANNs for automatic voltage regulation has been explored using recurrent neural networks (RNN) (Salem, *et. al*., 2003), (Bulic, *et. al*., 2007), (Karnavas, Y.L., and Papadopoulos, 2004) which show superior performance as compared to the conventional AVR with PSS. Extensive work has also been done on the use of ANNs in adaptive critic design (ACD) used for synchronous generator voltage regulation (IEEE Power Eng. Society,2006).

This work is an extension of (Salem, *et. al*., 2003) where different classes of input features to the MLP are explored.

3. A NEURO-CONTROLLED EXCITATION SYSTEM

3.1 System Model

A MLP is designed to function as the AVR and PSS of a single machine infinite bus (SMIB) power system. The system model is shown in figure 2. The parameters of the machines are given in the Appendix, table A1.

The excitation system consists of an ST1A configuration AVR (Kundur, 1994) and the PSS consists of two stages lead-lag network. The parameters of the PSS were obtained using phase compensation method coupled with trial and error approach to obtain a suitable gain. The AVR and PSS are shown in figure 3 and 4, respectively. The parameters for the SMIB system, AVR and PSS are given in Appendix A

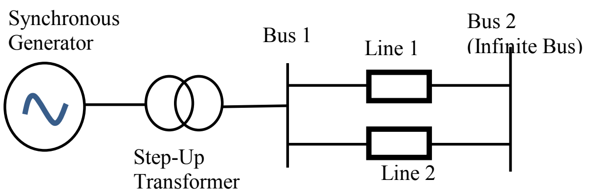

Fig 2: Single Machine Infinite Bus Model

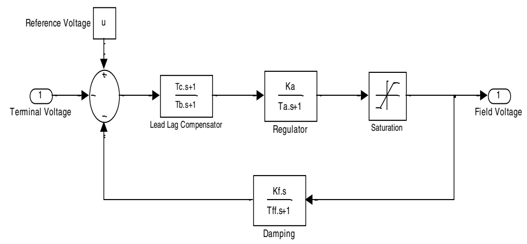

Fig 3: AVR and Regulator

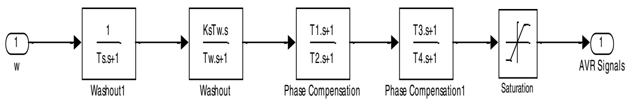

Fig 4: Power System Stabilizer

AVR and PSS parameter are given in Table A2.

3.2 MPL Design

The development of the ANNs comprises three tasks:

1. Determine the best class input signals.
2. Determine the optimum number of neurons in the hidden layer by incrementally growing the hidden layer and then evaluating the network's performance.
3. Determine the optimum value of the learning rates

The AVR function of the MLP is facilitated by back propagating the following error:

$$(V_{ref} - V_t) - \frac{d(V_{ref} - V_t)}{dt} \tag{10}$$

where V_{ref} is the reference terminal voltage signal, V_t is the terminal voltage of the generator , and $\frac{d(V_{ref} - V_t)}{dt}$ is the derivate of the voltage error.

The PSS function of the MLP is facilitated by the back propagation the following error:

$$w_{deviation} - \frac{dw_{deviation}}{dt} \tag{11}$$

where $w_{deviation}$ is the rotor speed deviation and $\frac{d(w_{deviation})}{dt}$ is the derivate of the speed deviation.

In order for the MLP to provide the function of both the AVR and PSS, the following error is back propagated through the network:

$$(V_{ref} - V_t) - kV * \frac{d(V_{ref} - V_t)}{dt} + w_{deviation} - kW * \frac{d(w_{deviation})}{dt} \tag{12}$$

where kV and kW are constants.

MLP networks are typically slow to converge and so the addition of the derivative to the error makes them appropriate for real-time control applications. A model of the neuro-controller is shown in figure 5

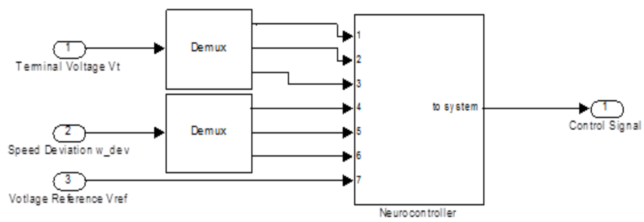

Fig 5: Neuro-controller Model

There neuro-controller consists of 7 inputs, 3 hidden neurons and 1 output. The terminal voltage, V_t, and the speed deviation, w_dev signals are delayed three times and input into the controller, where the TDL block stands for Time delayed. The voltage signal is delayed once and input into the controller, giving a total of 7 input signals. Through experimentation it was determined that a sample period of 20 ms will be used. The number of hidden layer neurons is determined empirically and so are the learning rates. A learning rate of 0.1 is used and kV and kW are set to 0.3

4. SIMULATION RESULTS

A 2100MVA generator is used in the Single machine infinite-bus (SMIB) system with a transmission line reactance of X = 0.6 p.u.

Figure 6 shows the tracking performance of the neuro-controller. A random set point voltage is generated every 15 seconds. Figure 6 shows that the neuro-controller has superior tracking performance to the conventional AVR and PSS. It is both faster and more accurate

The transient performance of the ANN is evaluated by subjecting the SMIB system (line 2) to a 3 phase-to-ground fault. Figures 7 and 8 show the terminal voltage and rotor speed deviation curves, respectively. The fault was self-cleared after 50ms and the line system returns to its original state. Figures 9 and 10 show the terminal voltage and rotor speed deviation curves, respectively. The fault is cleared by removing the line after 50ms. The above Figures were obtained when the system is operating at conditions P = 0.6 p.u. and pf = 0.85 lagging before the fault occurs. Figures 11 and 12 show the terminal voltage and rotor speed deviation curves when the SMIB system is operating at the conditions P = 0.7 p.u. and unity power factor. The fault was self-cleared after 50ms and the line system returns to its original state

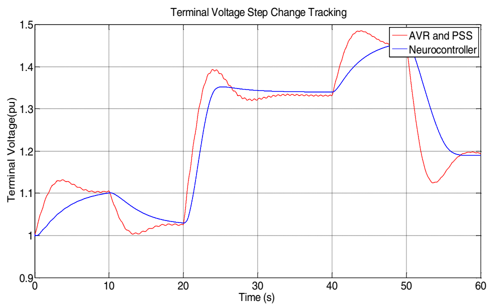

Fig 6: Terminal Reference Voltage Deviation Tracking

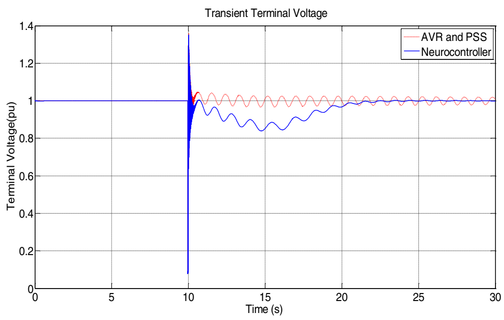

Fig 7: Terminal Voltage (P = 0.6p.u, pf = 0.85 lagging)

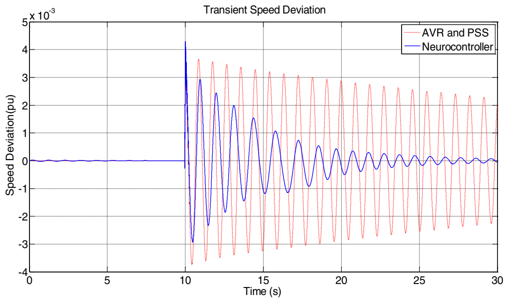

Fig 8: Rotor Speed Deviations (P = 0.6p.u, pf = 0.85 lagging

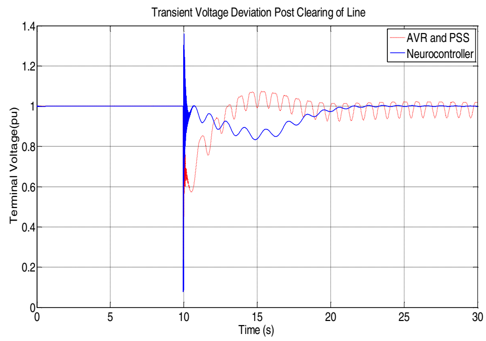

Fig 9: Terminal Voltage after the line 2 was removed (P = 0.6p.u, pf = 0.85 lagging)

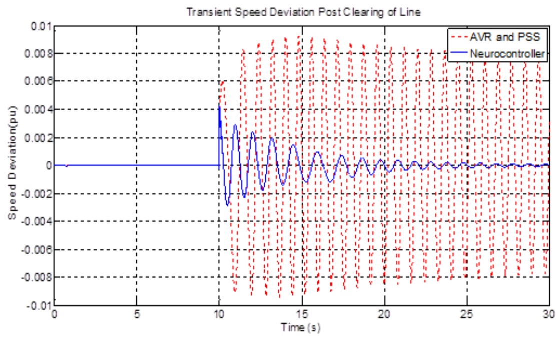

Fig 10: Rotor Speed Deviations after line 2 was removed (P = 0.6p.u, pf = 0.85 lagging)

Figures 7 and 8 show that the neuro-controller is able to recover quicker from the 3 phase-to-ground fault than the conventional AVR with PSS. Figures 9 and 10 show that the neuro-controller is robust than the conventional AVR with PSS. This is because this controller it is able to maintain the stability of the system even under severe disturbance.

Figures 11 and 12 show that the neuro-controller gives a better performance than the conventional AVR with PSS under heavy loading conditions.

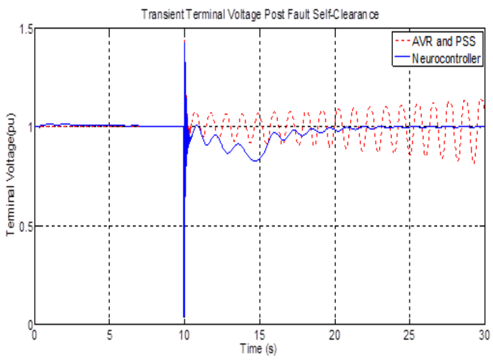

Fig 11: Terminal Voltage (P = 0.7p.u, pf = 1)

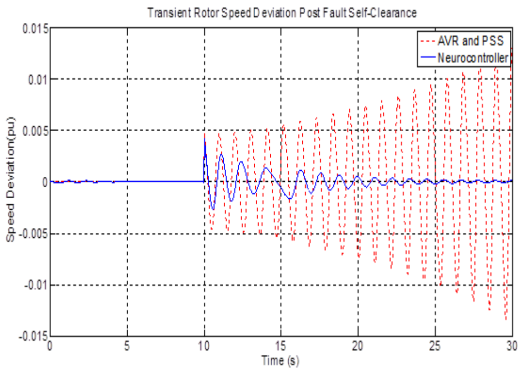

Fig 12: Rotor Speed Deviations after line 2 was removed (P = 0.7p.u, pf = 1)

5. CONCLUSIONS

The nonlinear nature of ANNs makes them attractive nonlinear controllers for nonlinear systems such as power systems. One can conclude that static MLPs are promising viable alternatives to conventional AVR and PSS excitation systems. They are robust and are able to guaranty the stability of the system under heavy load conditions. They are useful tools for the implementation of nonlinear controllers.

Future work entails research on an indirect approach to calculating the objective function that will facilitate even faster convergence. As well as examining the performance of the neuro-controller on a multi machine power system.

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APPENDIX

Table A1. Parameters of the synchronous generator

Parameter (Unit)	Value	Parameter (Unit)	value
P (MVA)	2100	Xl (pu)	0.15
Xd (pu)	2.0	Tdo' (s)	5
Xd' (pu)	0.245	Tdo'' (s)	0.031
Xd'' (pu)	0.2	Tqo' (s)	0.66
Xq (pu)	1.91	Tqo'' (s)	0.061
Xq' (pu)	0.42	Rs (pu)	0.003
Xq'' (pu)	0.2	H (s)	4

Table A2. AVR and PSS Parameters

Parameter (Unit)	Value	Parameter (Unit)	Value
Ka	190	Tw	4.58s
Ta	0.0001s	T1	0.25
Kf	1	T2	0.08
Tf	0.05	T3	0.25
Tb	1	T4	0.08
Tc	10	Ts	0.05
Ks	0.12		