Design of Simple Neuro-controller for Global Transient Control and Voltage Regulation of Power Systems

Mahdi Jalili-Kharaajoo and Rasoul Mohammadi-Milasi

Abstract: A novel neuro controller based simple neuro-structure with modified error function is introduced in this paper. This controller consists of two independent controllers, known as the voltage regulator and the angular controller. The voltage regulator is used to modify terminal voltage for the purpose of tracking a reference voltage. The angular controller is utilized to guarantee the stability of the system. In this structure each neuron uses a linear hard limit activation function that depends on the controlled variable and its derivatives. There is no need for parameter identification or any off-line training data. Two proposed controllers are merged by a smooth switch to build a complete controller. The effectiveness of the proposed novel control action is demonstrated through some computer simulations on a Single-Machine Infinite-Bus (SMIB) power system.

Keywords: Neural network based control, nonlinear system, power system stabilization, voltage regulation.

1. INTRODUCTION

Power systems are one of the most interesting fields for the application of various control theories. Although power system stability may be broadly defined according to different operating conditions [1], a significant problem under frequent consideration is the problem of transient stability. It concerns the maintenance of synchronism between generators following a severe disturbance. By the excitation control in a generating unit, transient stability can be greatly enhanced [2-5]. Another important issue of power system control is to maintain steady acceptable voltage under normal operating and disturbed conditions, which is referred to as the problem of voltage regulation [6-8]. From a practical point of view, voltage quality is a very important index of power supply in power system operation; so the post-fault value is expected to reach the normal value as closely as possible. To this end, a synchronous generator is equipped with an automatic voltage regulator (AVR), which is responsible for operating condition at various load levels.

The Artificial Neural Network (ANN) technology has matured enough to be applied successfully in many control fields [9]. However, its success will eventually depend on its ability to remove a major obstacle, i.e. the lack of a firm theory. There is no general theory available to assist the developer in the design of neural networks [10]. Because of the absence of a model, there is no complete theoretical basis to relate the ANN parameters to the characteristic of a system being controlled. The importance of studying neural network-based control architectures is revealed in the fundamental difficulties of current adaptive control techniques [11-13]. Adaptive control laws such as the model reference adaptive control and self-tuning regulator are nonlinear control laws, which are difficult to derive. Furthermore, the complexity grows geometrically with the number of unknown parameters. Artificial neural networks with their many interesting characteristics of learning, non-linearity, parallel processing, and etc. have been proposed for enhanced stabilizing control of synchronous generators [14-18].

In this paper, the transient stabilizer and voltage regulator is designed based on simple neuron structure Training of the proposed neuro-controller is performed on-line by the back propagation (BP) algorithm using a modified error function [16,17]. It has been shown that the controller obtained in this way acts in a superior manner to the classical power system stabilizer [16]. Moreover, it is simple to implement with no need for off-line training of the neural network, which is the most important characteristic of this neuro-controller in comparison with the other classical controllers.

To achieve transient stability as well as satisfactory post-fault terminal voltage level, a global transient

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stabilizer and voltage controller is designed. The control signal from the global controller is the average of the signals from the local control laws, i.e. transient stabilizer and voltage regulator, each weighted by the value of its operating region membership function [3, 19], since the membership function can be determined by direct measurable variables of power systems. The global controller designed in this way has the following interpretation. In the transient period, system states are far away from the equilibrium and so the primary control is to regulate them to enter a neighborhood of the equilibrium without large oscillations. Then in the post-transient period, around the point of equilibrium the voltage must be tuned to reach the prefault level. The membership function plays the role of appropriate weighting and smooth interpolation of the two controllers. One of the appealing abilities of the method is that the operating status is automatically distinguished by the membership functions, which are functions of directly measurable variables. Some computer simulations on a Single-Machine Infinite-Bus (SMIB) power system are provided to illustrate the performance of the proposed controller.

The rest of the paper is as follows. In Section 2 the model of a power system is presented. Section 3 describes the basic structure of neuro-controllers. We will present the design of the global control law in Section 4. Some simulations are provided in Section 5 and finally Section 6 concludes the paper.

2. POWER SYSTEM DYNAMIC

In this work, a complete model of a power system with seven differential equations is considered as the following [19]:

$$\begin{aligned}
\dot{\delta} &= \omega_0 \omega, \\
\dot{\omega} &= (T_m + g + k_d \delta - T_e)/2H, \\
\dot{\lambda}_d &= e_d + r_a i_d + \omega_0(\omega+1)\lambda_q, \\
\dot{\lambda}_q &= e_q + r_a i_q + \omega_0(\omega+1)\lambda_d, \\
\dot{\lambda}_f &= e_f - r_f i_f, \\
\dot{\lambda}_{kd} &= -r_{kd} i_{kd}, \\
\dot{\lambda}_{kq} &= -r_{kq} i_{kq},
\end{aligned} \tag{1}$$

and the governor used in this study has the following equation:

$$g(s) = [a + b/(1 + sT_g)]\delta(s). \tag{2}$$

The fault considered in this paper is a symmetrical three-phase short circuit fault, which occurs on the transmission lines. Once the fault on the transmission lines is removed, the breakers of the lines are opened.

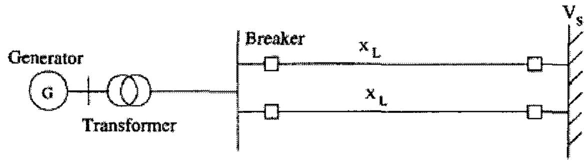

Fig. 1. A single machine infinite bus power system.

3. STRUCTURE OF NEURO-CONTROLLERS

In this section, the general structure of local neuro-controllers, i.e. the transient stabilizer and voltage regulator, will be presented. For the sake of simplicity, the complete structure of the Neuro-Voltage Regulator (neuro-VR) is discussed. The other local controller, known as the neuro-transient stabilizer, can be designed similarly.

In order to regulate generator terminal voltage to the prefault value, a simple neuro-VR is used [16,17]. The overall control system with the proposed neuro-controller consisting of one neuron is shown in Fig. 2. The neuro-controller uses a linear hard limit activation function and a modified error feedback function.

The neuro-controller uses a simple procedure to update its weight on-line. There is no need for any off-line training. There is no need for parameter identification or reference modeling. It uses the sampled values of the system output to compute the error using the modified error function. This error is back propagated through the single neuron to update its weight. Then, the output of the neuro-controller is computed, which is equal to the neuron weight. The neuro-controller output can be derived as:

$$u(t) = W(t), \tag{3}$$

$$W(t) = W(t-1) + \eta \times WCT(t), \tag{4}$$

where WCT is the neuron weight correction term based on the modified error function. $W(t)$, $u(t)$, η are neuron weight, neuron output and the learning rate respectively.

Based on (3) and (4), the neuro-controller model in s-domain can be obtained. In time domain, (4) can be written as:

$$W(t) - W(t - \Delta t) = \eta \times WCT(t). \tag{5}$$

Dividing (5) by Δt, we have:

$$\frac{W(t) - W(t-\Delta t)}{\Delta t} = \frac{\eta \times WCT(t)}{\Delta t}. \tag{6}$$

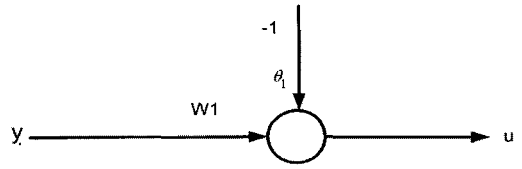

Fig. 2. Single neuro configuration.

Using the differential form, (6) can be written as:

$$\frac{dW(t)}{dt} = \eta_1 \times WCT(t) \quad ; \quad \eta_1 = \frac{\eta}{\Delta t}. \tag{7}$$

Representing (7) in s-domain results in:

$$sW(t) = \eta_1 \times WCT(t). \tag{8}$$

From (3) and (8), we have:

$$U(s) = \frac{\eta_1 \times WCT(t)}{s}. \tag{9}$$

The general form of the weight correction term is:

$$WCT(s) = R(s) - C(s)f(s), \tag{10}$$

where *R(s)*, *C(s)* and *f(s)* are reference input, system output and feedback function, respectively.
A complete model of the proposed neuro-controller in s-domain is shown in Fig. 3, where *G(s)* represents the controlled system.

In order to obtain the best parameters of the controller, first a simplified linear model of the synchronous generator is used [16,17]. The neuro-controller as a voltage regulator (VR) with the simplified machine model is shown in Fig. 4. The proposed modified feedback function in this case is:

$$f(s) = 1 + k_v s. \tag{11}$$

Assuming that $k_v = 0$ (unity feedback), the system response to a 0.05pu step change in reference input for two values of η_1 is shown in Fig. 5 ($\eta_1 = .5, \eta_1 = 2$). As indicated in Fig. 5, the overall system behaves as a stable second order system. But as η_1 increases, the system is more oscillatory. This is an expected result even for a complicated structure neural network [16].

To improve the performance of the neuro-controller, which is trained on-line by the BP algorithm, a modified function was introduced in [5,7]. The effect of the modified function on the neuro-controller performance based on analytical studies is described below.

Assuming that the neuro-controller uses the proposed feedback function f(s), (11), in its training, a critically damped response to a step change in reference input can be obtained for [22]:

$$k_v = \frac{2\sqrt{\eta_1 T'_{do}} - 1}{\eta_1}. \tag{12}$$

According to the above formula, for $\eta_1 = 500$, $T'_{do} = 6.9$, then $k_v = 0.23$, for a critically damped response. This critically damped response is shown in Fig. 6 for a 0.05pu step change in reference input. Also, other values for η_1 and k_v for a critically damped response can be obtained. These values are:

$$\eta_1 = 200, k_v = 0.37, \eta_1 = 10, k_v = 1.56.$$

The system response corresponding to these values is also presented in Fig. 6. It is clear from this figure that as η_1 increases the response is improved. So, the proposed values for η_1 and k_v are:

$$\eta_1 = 500,\ k_v = 0.23.$$

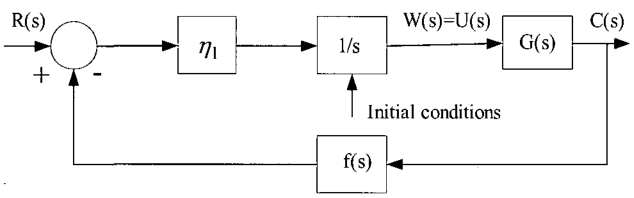

Fig. 3. Neuro-voltage controller model in s-domain.

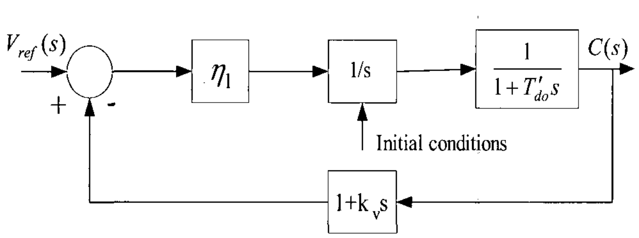

Fig. 4. Neuro-voltage controller as an AVR for a simple model of the synchronous generator.

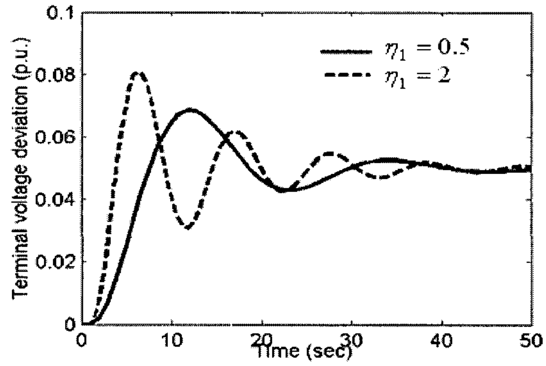

Fig. 5. Neuro-voltage controller performance using unity feedback function for a simple model of the synchronous generator.

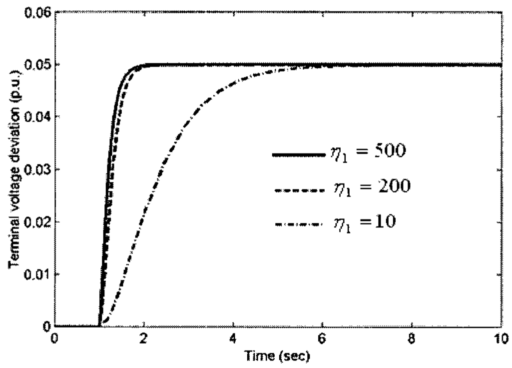

Fig. 6. Neuro-voltage controller performance using modified error function for a simple model of the synchronous generator.

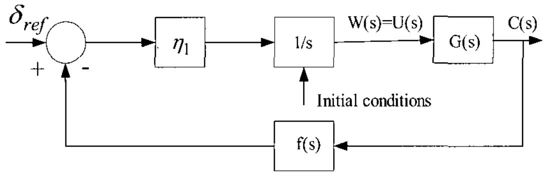

Fig. 7. Neuro-transient stabilizer model in s-domain.

The structure of neuro-transient stabilizer is similar to neuro-VR, which is represented in Fig. 7. δ_{ref} is the reference angle, which can be calculated from the following equation:

$$V_{ref} = \sqrt{\frac{P_e^2 x_s^2}{V_s^2 \sin^2 \delta_{ref}} + \frac{V_s^2 x_d'^2}{x_{ds}'^2} + \frac{2 x_s x_d' P_e \cos\delta_{ref}}{x_{ds}' \sin\delta_{ref}}}. \quad (13)$$

It is remarkable that x_s, x_{ds}, x_d', and x_{ds}' vary during fault occurrence, so the value of δ_{ref} will be diverse for prefault, fault, and post-fault periods. With a similar training procedure for neuro-VR, the following parameters are obtained for the neuro-transient stabilizer:

$\eta_l = 350, \ k_v = 0.49$.

So, the two local controllers, i.e. transient and voltage controllers, are obtained based on a simple neuro structure. This simplicity is the main advantage of this controller in comparison with the other classical controllers designed for power systems. In the next section, the construction of a global controller will be presented.

4. DESIGN OF GLOBAL CONTROL LAW

In the previous section, the local controllers, i.e. transient stabilizer and voltage regulator, were designed based on a simple neuron structure. The global control law is the average of the signals from the local controllers, each weighted by the value of its operating region membership function, since the membership function can be determined by direct measurable variables of power systems. Indeed, the controller structure for the synchronous generator is obtained by the combination of two neuro-controllers, which receives feedback concerning output voltage and angle. We use the following trapezoid-shaped like membership functions that are able to indicate different operating stages [3,19]:

$$\mu_\delta = 1 - \frac{1}{1+\exp(-120(z-0.08))}, \quad (14)$$

$$\mu_v = 1 - \mu_\delta, \quad (15)$$

where μ_δ and μ_v are corresponding membership functions for transient and voltage controllers, respectively, where

$$z = \sqrt{a_1 \Delta\omega^2 + a_2 (\Delta V)^2} \quad (16)$$

and

$$\Delta\omega = \omega - \omega_o \quad (17)$$

where a_1, a_2 are positive design constants providing appropriate scaling, which can be chosen according to the different sensitivity requirements of power frequency and voltage.

Membership function (14) is plotted in Fig. 8. It can be seen that $\mu_\delta(z)$ gets its dominant value when z is far away from the origin, which corresponds to the transient period. On the other hand, $\mu_v(z)$ does so when z is close to the origin, which indicates the post-transient period. Since the membership function values are determined by the directly measurable variables, ω and V_t, the fault sequence, need not be known beforehand.

Therefore, the whole operating region is partitioned into the following two subspaces by the membership functions, where S_1 indicates the transient period and S_2 indicates the post transient period.

$$\begin{cases} S_1 = \{(\Delta\omega, \Delta V_t) | \mu_v \le \mu_\delta\} \\ S_2 = \{(\Delta\omega, \Delta V_t) | \mu_\delta \le \mu_v\} \end{cases} \quad (18)$$

The characteristic function of each subspace $S_l (l = 1, 2)$ is defined by:

$$\tau_l = \begin{cases} 1 & z \in S_l \\ 0 & \text{otherwise}. \end{cases} \quad (19)$$

Note that $\tau_1 + \tau_2 = 1$.

It should be pointed out that ω and V_t are chosen as the index variables in (16) since they sufficiently represent operating status for the problem of transient stability and voltage regulation. If the problem under consideration is voltage stability, reactive power could be included in the index.

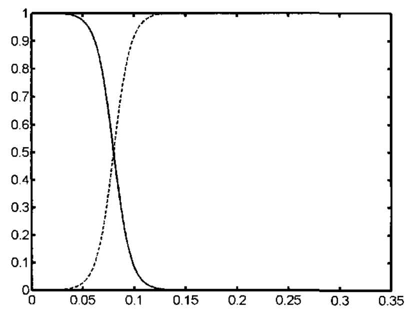

Fig. 8. Membership function, μ_δ "___" and μ_v "- - -"

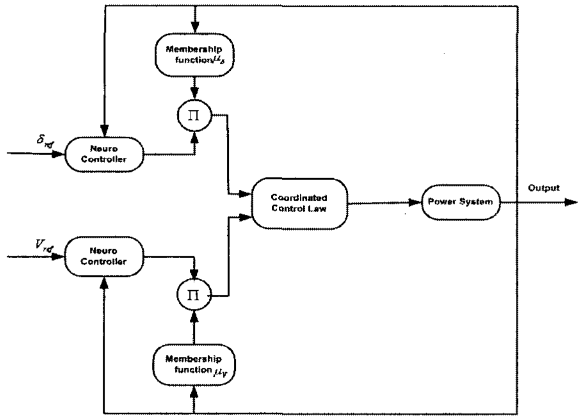

Fig. 9. Global controller for synchronous generator.

Similarly the proposed method can be extended to other power system control issues. The chosen membership functions have a trapezoid-like shape, which is well known in fuzzy control to separate operating conditions. The system performance is not sensitive to different parameters a_1 and a_2 [3].

The global control law is the average of the individual control laws, weighted by the operating region membership functions, i.e., the input u_f takes the form:

$$u_f = e_\delta \mu_\delta + e_v \mu_v, \tag{20}$$

where

$$e_\delta = \delta - \delta_{ref}, \tag{21}$$

$$e_v = V_t - V_{ref}. \tag{22}$$

Fig. 9 depicts the block diagram of proposed global control law for power systems.

5. SIMULATION RESULTS

In this section, some computer simulations are provided to study the performance of the proposed global control law. The simulations are carried out using SIMULINK and MATLAB packages. The prefault conditions of the system are:

$$\delta_o = 30^o, \qquad P_{mo} = .7, \qquad V_{to} = 1.$$

To investigate the performance of the proposed controller, consider a symmetrical three-phase short circuit fault in the middle of one of the transmission lines when the following sequence occurs:

Stage 1: The system is in the prefault steady states;
Stage 2: A fault occurs at $t = 20.1\,\text{sec}$;
Stage 3: The fault is removed at $t = 20.2\,\text{sec}$;
Stage 4: The system is in the post-fault state.

When the fault is removed, the breakers act and the affected line is opened.

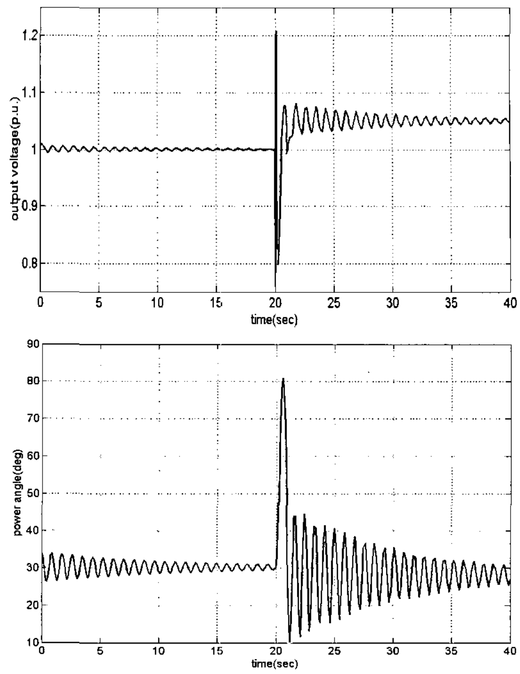

Fig. 10. System response to a three-phase to ground fault with the global neuro-controller.

The responses of the closed-loop system with the proposed controller for the above fault are depicted in Fig. 10. In this case, in the transient period, the transient controller is the dominant control action and in the post transient period, the voltage controller is the dominant one. As it can be seen, the post-fault terminal voltage value is regulated to its prefault value and the stability of the system is very good. This controller can stabilize the closed-loop system and also regulate the terminal voltage to its prefault value. Although the controllers proposed in [3,17,19] could provide a global control law for transient stability and voltage regulation of power systems, the main advantage of the proposed method in this paper is the simplicity of the design of local controllers, which can be applied for a more complicated model of power systems.

6. CONCLUSIONS

In this paper, a global control law for transient stabilization and voltage regulation of power systems was presented. The transient controller based on a simple neuron structure, which requires neither parameter identification nor off-line training, was designed. If only the transient controller is used, the post-fault terminal voltage may differ from its prefault value, which is not desired for power systems. So, a neuro-voltage regulator was designed similarly. To achieve the global control action, we used a membership function that was a function of measurable parameters of the system (rotor relative speed and generator terminal voltage). The simulation results of a three-phase short circuit fault in a SMIB power system, which occurred on the middle of one of the transmission lines, showed the effectiveness of the proposed global controller.

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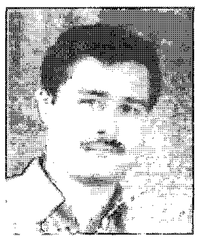

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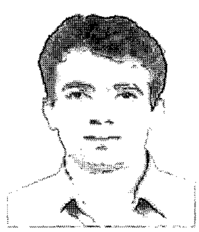

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