AN ADAPTIVE NEUROCONTROLLER FOR SPEED CONTROL OF A SYNCHRONOUS GENERATOR

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***Abstract* — Neural networks have shown great promise in many areas of engineering. In this paper, we present a newly designed neural control system that consists of three neural networks cascaded together, one representing the inverse model of the speed-governing and turbine system, another identifying the dynamics of the synchronous generator, and a third being part of the controller. The inverse model is achieved with a multilayer feedforward neural network trained in batch mode through back-propagation learning. Once the network is trained, its weights and biases will be fixed. The dynamics of the synchronous generator is identified on-line while the generator is operating. The weights of the neurocontroller are determined by sweeping back the control error. Usually this updating process has a lower frequency than the identification process to ensure the stability of the entire control system. The neurocontroller was applied to a multi-machine power system and some simulated results are presented.**

1. Introduction

Artificial neural networks (ANN) can be used to solve highly complex nonlinear problems. It has been reported [1] that generalized neural networks containing multilayer neural networks and dynamic elements as subsystems can be used to identify and to control a large class of nonlinear dynamic systems. Using such trainable networks as building blocks, one can formulate multilevel intelligent controllers for dynamic systems of any complexity. Neural networks used in control systems are placed in a closed loop with the controlled system, hence training of the networks must be performed on-line. Specific training methods to be employed depend on the arrangement of the neurocontroller in the control loop. There are five generic approaches to design a neural controller[2,3]. Specifically, they are supervised control, direct inverse control, neural adaptive control, back-propagation of utility, and adaptive critic. A neural adaptive control approach will be utilized in this paper.

In order to minimize the load-frequency transients, a layered neural network is trained to control the steam admission valve of a turbine-generator system[4]. To control a turbogenerating system, a hierarchical architecture of neural networks has been proposed in [5]. In paper [6], an artificial neural network, functioning as a power system stabilizer, has been used to map the inverse dynamics of the controlled plant of a one-machine infinite bus system. During training, the ANN is presented with input-output pairs of the plant with an adaptive PSS tuned in. In operation, the ANN is fed with the desired output of the synchronous machine and the output of the ANN is used as the control signal to the controlled plant.

This paper is mainly concerned with speed-control of a synchronous generator in a multimachine environment. The problem is divided into two parts, one for identifying the process and the other for controlling it. Plant nonlinearities and hardware limits will be integrated into the neural networks.

2. Modeling of a Synchronous Generator

Figure 1 shows an approximate nonlinear model of a mechanical-hydraulic speed-governing controller and a hydroturbine. It consists of a speed governor, a pilot valve and a servomotor, a distributor and a gate servomotor, as well as a governor controlled gate. It can be shown that the system is described by a nonlinear mapping function,

$$\begin{aligned} y_p(k+1) = f[&y_p(k), y_p(k-1), \ldots, y_p(k-n+1); \\ &u(k), u(k-1), \ldots, u(k-m+1)] \end{aligned} \tag{1}$$

where $u(k) = SR - \omega(k)$ and $y_p(k) = P_m(k)$, and SR = speed reference. $[u(k), y_p(k)]$ is the input-output pair of the system at discrete time k, and $m \le n$.

The dynamics of the rest of the generating system can be expressed as

$$\begin{aligned} \omega(k+1) = h[&\omega(k), \omega(k-1), \ldots, \omega(k-n+1); \\ &P_m(k-1), \ldots, P_m(k-m+1); \\ &I(k), I(k-1), \ldots, I(k-p+1); \\ &\varphi(k), \varphi(k-1), \ldots, \varphi(k-q+1); \\ &\theta(k), \tau(k)] + \beta P_m(k) \end{aligned} \tag{2}$$

where h is a nonlinear function; current I and flux φ are vectors, $\theta(k)$ is a vector of system parameters and $\tau(k)$ the network topology. If a one-step ahead output of the nonlinear system can be predicted, the present input signal $P_m(k)$ can then be calculated from (2) as well.

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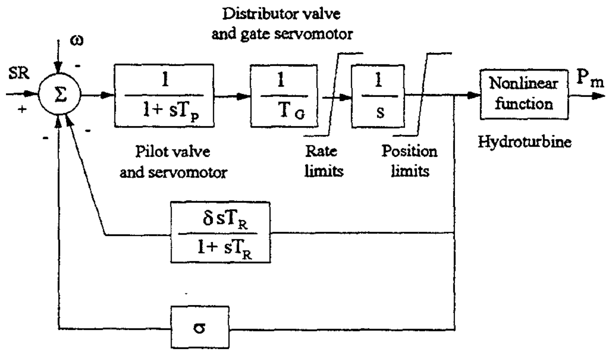

Fig. 1 Mechanical-hydraulic speed-governing system and hydroturbine

3. Mapping Approximation by Neural Networks

The system shown in Figure 1 is a SISO nonlinear one described by a nonlinear function (1). From practice we understand that the system produces bounded outputs for bounded inputs and that the input and output relation is deterministic. Assuming that the inverse dynamics of the system can be expressed as

$$u(k) = f^{-1}[y_p(k+1), y_p(k), \ldots, y_p(k-n+1); \quad u(k-1), u(k-2), \ldots, u(k-m+1)] \tag{3}$$

where f^{-1} denotes the inverse function of f.

A multilayer feedforward generalized neural network is chosen to represent the system dynamics of (3) with $m=4$ and $n=4$. The selection of these numbers is made according to the order of the corresponding linear model though larger numbers could also be used. A two-layer feedforward neural network was trained with *401* input/output patterns. The first layer has *17* neurons and the output layer one neuron, with both layers using the tan-sigmoid transfer function. A low-peak-factor multi-frequency input signal was chosen as excitation to the system. Suppose that the following frequencies, i.e., $k_1/T, k_2/T, \ldots, k_n/T$, are to be excited, where T is the period of the input signal $x(t)$ and $k_1, k_2, \ldots, k_n$ are integers. The signal is given by

$$x(t) = \sum_{i=k_1}^{k_n} \sqrt{(2P_{k_i})} \cos\{2\pi(k_i/T)t + \phi_{k_i}\} \tag{4}$$

where P_{k_i} is the relative power of the k_i-th harmonic and $k_1, k_2, \ldots, k_n$ do not have to be consecutive. And ϕ_{k_i} can be determined by $(\pi k_i^2/n)$ where n is the total number of the harmonics in the signal. An input of this design is reported to be superior to the pseudo-random binary sequence[7].

The mathematical representation for the dynamics of the generator has been established in section II. Due to the interface with other generating units through the transmission network, this model given in (2) is characterized by nonlinearities, shifts of system parameters, and changes of network topology. Physically these changes are implicitly reflected in electric quantities at the terminal of the generating unit. Although it is not impossible to identify the dynamics of the generator in batch mode, it would be very tedious to do as the input patterns have to cover all possible combinations of all state variables that have a direct effect on its operation. Also the number of neurons at the first layer will be dramatically increased. On-line identification excludes these difficulties. The identification of this part of the system will be further discussed in a later section when a simulation study is carried out.

4. Design of the Neurocontroller

On the basis of indirect adaptive control [1] using a reference model to guide the controlled plant to follow a prespecified trajectory, the proposed approach combines merits of both batch mode and on-line identification schemes in designing a neural controller. As the inverse dynamics of part of the controlled plant is achieved before hand, the task of on-line identifying the entire plant is greatly reduced. Figure 2 illustrates a conceptual overall structure of the neurocontroller to be designed where N_s^i and N_s^c denote neural networks for identification and control, respectively; and N_{-g}^i denotes the inverse mapping of the system shown in Figure 1.

The dynamics of the generator is a high order nonlinear system given by (2). For such systems, it is difficult to define the design objectives such as those defined in terms of "quadratic performance index" in the linear optimal control theory. Model reference adaptive control or linear model following control can be used to avoid these difficulties. In this section, a multivariable linear system is designed for model reference adaptive control of the generating unit using neural networks.

Assume that an ideal speed-governing and turbine system has the following transfer function

$$\frac{P_m}{\omega_{ref} - \omega} = \frac{K_g}{1 + sT_g} \tag{5}$$

where ω_{ref} is a speed reference input to the governor, T_g the time constant of the system, and K_g the DC gain. This results in a differential equation given by

$$\dot{P}_m = -K_g\omega/T_g - P_m/T_g + K_g\omega_{ref}/T_g \tag{6}$$

The generator dynamics can be expressed as

$$\dot{\omega} = -D\omega / 2H + P_m / 2H - P_e / 2H \quad (7)$$

The corresponding state space equations of the system can be expressed by

$$\dot{x} = Ax + Bu_m \quad (8)$$

$$y = Cx \quad (9)$$

where $x(t) = [\omega(t)\ P_m(t)]^T$ and $u_m = [P_e\ \omega_{ref}]^T$.

The upper part of Figure 2 shows this reference model, where the output $\omega(t)$ is sampled at a sampling rate of $1/T$ and compared with the true output of the plant. Note that $P_e = real(V\overset{*}{I})$ is determined by the terminal current and voltage.

Consider the problem of controlling the overall system of the hydro-generating unit connected to a power system. The objective of adaptive control is to make the controlled system behave as desired. We assume that the unknown function $h(\cdot)$ as given in (2) is approximated by a multilayer neural network N_s^i. And that the inverse model is approximated by another neural network N_{-g}^i which cancels the dynamics of the governor(GOV). The reference model is given by (8,9) where $u_m(t)$ is a bounded input. At time instant k, the reference model is simulated with reference $r(t)$ and system state variable $P_e(t)$ as inputs, and its output is sampled and compared with that of the generator. The error e_c is then swept back to determine N_s^c. Finally, the manipulated output $u(k)$ of the neurocontroller is obtained by using N_s^c and N_{-g}^i as shown in Fig. 2. When a transient ends, $u(k)$ settles down to a new speed reference (SR), a new setpoint according to which the gate is repositioned.

5. Simulation Studies

The designed neurocontroller was applied to a multiple machine power system as shown in Figure 3. Detailed system parameters and machine data are given in [8]. A system disturbance such as three-phase fault, load change or change of system topology can be initiated during the simulation process.

To demonstrate the performance of the neurocontroller, some primitive results from simulations of two scenarios are presented as follows. Scenario #1 simulates an external disturbance, i.e., a three-phase to ground fault on the line 1-4 near bus 1. The fault was cleared after six cycles and the network was restored to the prefault configuration. Figure 4 shows simulated speed responses of the test machine with the neurocontroller switched in or out. Some improvement in damping is shown with the neural control scheme. Figures 5(a) and 5(b) illustrate a situation where the reference input has a one percent ramp change that lasts about two seconds and returns to its original value thereafter. It is shown in Fig. 5(b) that the speed response settles down after one cycle of oscillation.

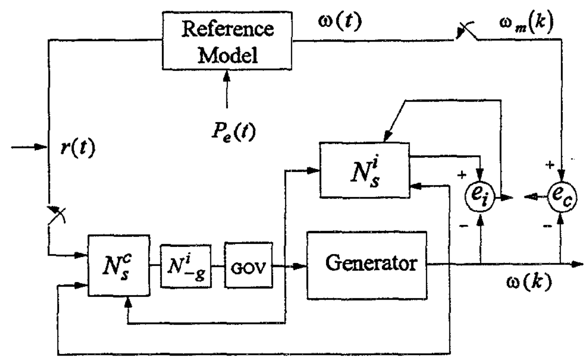

Fig. 2 Conceptual structure of the neurocontroller

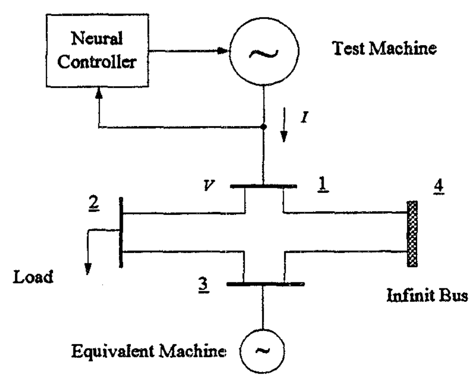

Fig. 3 Simulated multi-machine power system

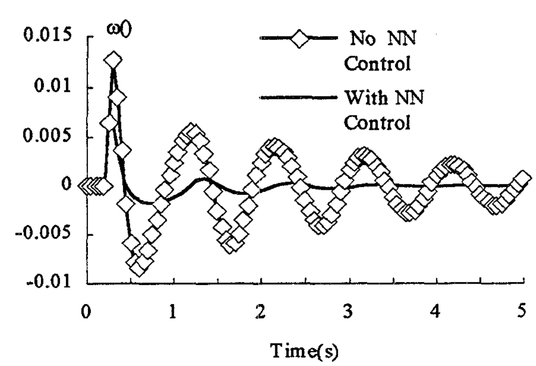

Fig. 4 Speed responses of generator #1 following an external three-phase fault near the terminal

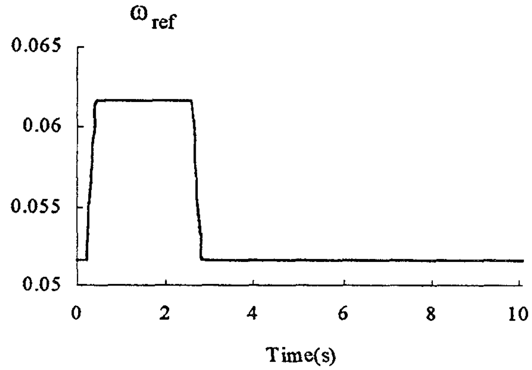

Fig. 5(a) Ramp change of reference input

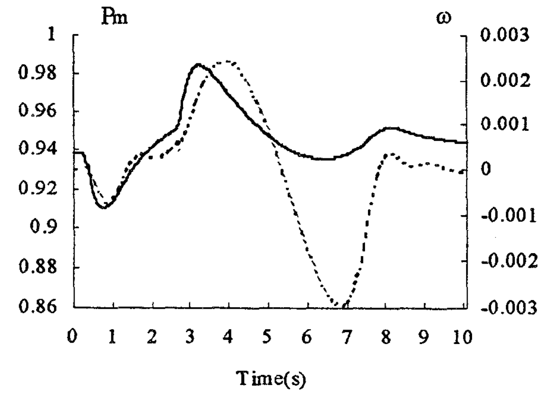

Fig. 5(b) Responses to change of reference input
solid line = mechanical power
dotted line = machine speed

6. Conclusions

This paper has been principally concerned with the design of a neurocontroller for speed control of a synchronous generator. Since the dynamic system is divided into two subsystems, and only the second subsystem needs on-line identification, the computational overhead is greatly reduced in identification and controller updating. Another advantage is that system nonlinearities, disturbances and changes of parameters can all be implicitly accounted for in the control process due to the benefits of on-line identification. This also avoids the difficulties in exhausting all possible combinations of operating conditions for batch mode identification of a generating unit. Primitive results have shown that the neurocontrller can enhance transient stability.

7. Acknowledgment

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