EXCITATION CONTROL IN POWER SYSTEMS

An electric power system contains thousands of interconnected electric elements. Many elements are highly nonlinear and some of them are combinations of electrical and mechanical parts. Power systems have thus developed into complex operating and control systems with various kinds of unstable characteristics (1). Because these systems are spread over vast geographical areas, some of which span over entire continents, they are subject to many different types of disturbances. With the advent of interconnection of large electric power systems, many new problems have emerged. Two examples are the oscillations of the subsystems of a large interconnected power system against each other and the subsynchronous tortional oscillations of turbines in a steam power plant with capacitor-compensated transmission lines (2).

A sample five machine power system configuration is shown in Fig. 1. When this system is disturbed, multimode oscillations arise because of the different sizes of the generators and the network configuration. These oscillations are generally analyzed in three main oscillation modes (i.e., local, interarea, and intermachine modes). Depending upon their location in the system, some generators participate in only one

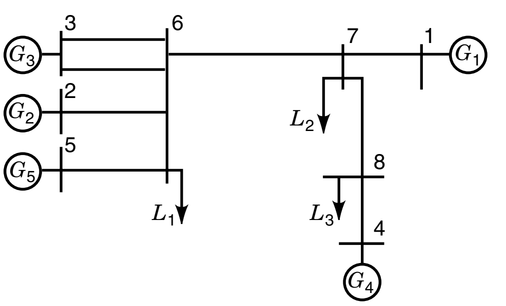

Figure 1. A five-machine power system configuration.

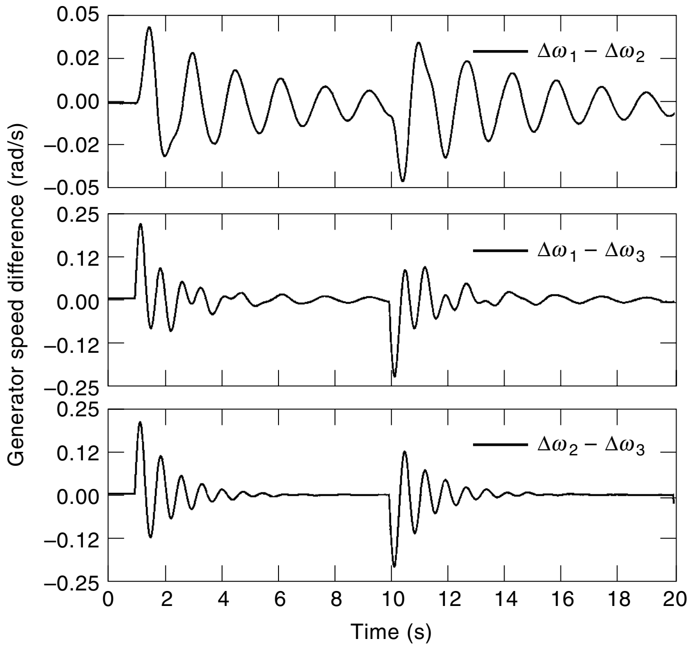

Figure 2. Multimode oscillations of the five-machine power system.

oscillation mode, whereas others participate in more than one mode (3). The multimode oscillations can be clearly observed in Fig. 2.

The definition of stability, as applied to power systems may be stated as follows (4):

> If the oscillatory response of a power system during the transient period following a disturbance is damped and the system settles in a finite time to a new steady state operating condition, the system is stable. Otherwise, it is considered unstable.

A small signal perturbation model around an equilibrium point can be considered for dynamic stability studies, and the system can be described by linear differential equations. However, for transient stability analysis and control design, the power system must be described by nonlinear differential equations. A set of *seventh*-order equations for a synchronous alternator is given in the appendix.

Over the years, considerable efforts have been devoted to improving power system stability in various ways (5–8). These attempts can be divided into three broad groups:

- Generator excitation control,
- Generator input power control, and
- System operating condition and configuration control.

For a particular problem, any one or more of these three methods can be employed. Among these methods, excitation control is preferred for the following reasons:

- Generally electrical systems have much smaller time constants than mechanical systems,
- Electrical control systems are more economical and easier to implement than mechanical control systems,
- Additional equipment required operates at low power level, whereas other methods (such as resistor braking and capacitor switching) need a much higher power level.

Synchronous machine excitation control and its role in improving power system stability have been an important topic of investigation since the 1960s. Effectiveness of damping produced by the excitation control has been demonstrated both by simulation and field tests (9,10). The main objective is to achieve an acceptable voltage profile at the consumer terminal. High gain, short time constant, and high ceiling voltage excitation control are among the characteristics of this control loop. An AVR and exciter model from IEEE standard is given in the appendix. Although these result in increasing both the steady state and transient stability limits of the system (11), they can also introduce a detrimental impact upon the dynamic stability of the power system. Oscillations of small magnitude and low frequency often persist for long periods of time and in some cases present limitations on power transfer capability.

To overcome this problem, a supplementary stabilizing signal has been proposed to enhance the dynamic performance of the power system. To date, many of the major electric power plants in large interconnected systems are equipped with this supplementary excitation control, commonly referred to as Power System Stabilizer (PSS). The purpose of the supplementary stabilizing signal is to enhance system damping by producing a torque in phase with the speed. In the conventional arrangement, the stabilizing signal is usually derived by processing any one of a number of possible signals (e.g., speed, acceleration, power, frequency). The output of the PSS (i.e., the stabilizing signal) is introduced into the excitation system at the input to the AVR/exciter along with the voltage error. To improve the power system performance and stability, various approaches based on linear optimal, *H*-infinity, variable structure, rule-based, fuzzy logic, neural network and adaptive control have been proposed in the literature to design a PSS. This article provides an overview of these techniques. To obtain further information, one should refer to the corresponding references.

FIXED PARAMETER CONTROLLERS

The most commonly used PSS, referred to as the Conventional PSS (CPSS), is a fixed parameter analog-type device with the following linear transfer function:

$$U_{\text{pss}}(s) = K_s \frac{1+sT_1}{1+sT_2}\frac{1+sT_3}{1+sT_4}\frac{sT_5}{1+sT_5}\Delta P_e(s) \tag{1}$$

The CPSS is based on the use of a transfer function designed by the linear control theory (12) to the system model linearized at a preassigned operating point. It contains a phase compensation network for the phase difference from the excitation controller input to the damping torque output (i.e., the gain and phase characteristics of the excitation system, the generator and the power system, which collectively determine the open-loop transfer function). By appropriately tuning the phase and gain characteristics of the compensation network during the simulation studies at the design stage and further during commissioning, it is possible to set the desired damping ratio. Various tuning techniques have been introduced to tune the CPSS parameters effectively (13).

CPSSs are widely used in the power system these days, and they have improved power system dynamic stability. The CPSS is designed for a particular operating point for which the linearized transfer function model is obtained. The characteristics of the plant are nonlinear. For example, the gain of the plant increases with generator load. Also, the phsae lag of the plant increases as the power system becomes stronger. Because of the high nonlinearity, the wide operating conditions, and the unpredictability of perturbations in a power system, the CPSS, a linear controller, generally cannot maintain the same quality of performance under all conditions of operation. The parameter settings of a CPSS are a compromise that provides acceptable, though not optimal, performance over the full range of operating conditions. The linear optimal control (14) and H_∞ (15,16) based PSSs also fall in the fixed parameter controller category. The design of these controllers is done off-line on a linearized model of the power system. Using the state and/or output feedback, gains that minimize a certain performance index are determined. The H_∞ control design differs from the linear optimal control design in that it provides for uncertainties over a prespecified range in the system parameters and disturbances. However, because of the fixed feedback gains, variations in the system structure and/or characteristics cannot be tracked. It is thus not possible to provide optimal performance over the entire operating range. To solve the parameter tracking problem, design of a CPSS based on the variable structure control theory has been proposed (17). Although it is an elegant design technique, its design procedures share some commonality with that of linear optimal control. Because of the absence of any formal procedures, the weights in the performance index of the linear optimal control and the weights of the switching vector for the variable structure algorithm have to be determined by trial and error.

RULE BASED AND FUZZY LOGIC CONTROLLERS

Unlike the conventional control techniques, which require complicated mathematical models derived from a deep understanding of a system, exact equations and precise numeric values, fuzzy logic control techniques are rule-based systems. In these systems, a set of fuzzy rules represents a control decision mechanism to adjust the effects of certain causes coming from the controlled system (18,19). The basic feature of the fuzzy logic control is that a process can be controlled without the knowledge of its underlying dynamics. The operator can simply express the control strategy, learned through experience, by a set of rules. These rules describe the behavior of the controller using linguistic terms. The controller then infers the proper control action from this rule base, thus playing the role of the human operator. The theme of the fuzzy logic is to relate the numeric variables to linguistic variables, where dealing with the linguistic variables is closer to the human spirit. Each linguistic variable represents a fuzzy subset. Each fuzzy subset has a membership function that defines how far this measurement belongs to this linguistic variable. Figure 3 shows the basic configuration of a fuzzy logic controller (FLC), which is composed of four principal components: fuzzification module, knowledge, base, inference mechanism and a defuzzification module.

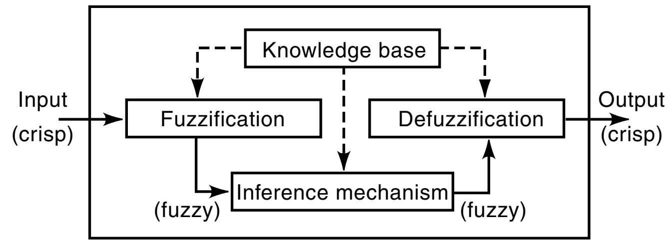

Figure 3. Basic structure of fuzzy logic controller.

Some of the major features of the FLC follow:

- This method does not require the exact mathematical model of the system.
- It offers ways to implement simple but robust solutions that cover a wide range of system parameters and that cope with major disturbances.
- The simplicity of the concept makes it easy to implement and requires less software code to write.
- Because the control strategy mimics the human way of thinking, the experience of a human operator can be implemented through an automatic control method.

Satisfactory results have been obtained with PSSs designed based on FLC (20,21). Although the FLC introduces a good tool to deal with complicated nonlinear and ill-defined systems, it suffers from the drawback of parameter tuning for the controller. Proper decision rules cannot easily be derived by human expertise for too complex systems, making fine-tuning or achieving the optimal FLC not a trivial task. Some significant operating conditions (i.e., disturbances or parameter changes) may be outside the expert's experience. Design and tuning of an FLC for a multiinput multioutput system is extremely tedious. Often the approach adopted is to define membership functions and decision rules subjectively by studying an operating system or an existing controller. Genetic algorithm, a global optimization method, can be used to help in the optimization and tuning of an FLC. However, it also has its limitations because it can fall into a local optimal point if the parameters are not properly selected.

NEURAL NETWORK-BASED CONTROLLERS

Artificial neural networks (ANNs) attempt to achieve good performance by interconnecting simple computational elements. They offer many advantages by virtue of their characteristics, which are the capability to synthesize complex and transparent mappings, increased speed resulting from the parallel mechanism, robustness and fault tolerance, and adaptive adjustability to the new environment. The success of ANNs to control unknown systems under significant uncertainties makes them very attractive. Among the many properties of a neural network, the property that is of primary significance is the ability of the network to learn from training data and to improve its performance through learning. Basic classes of learning paradigms are the supervised learning, reinforced learning, and unsupervised learning. There are different control schemes to train a neural network to control a plant that is too complex, or about which very little is known.

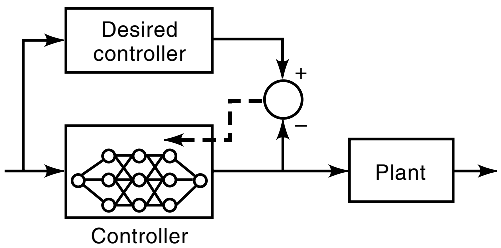

Figure 4. Copying an existing controller with a network.

In a typical control problem, the desired plant output may be known but not the desired controller output (i.e., the control signal). Three basic ways in which the training information required for supervised learning can be obtained follow:

- Copying an existing controller (22). This approach, as shown in Fig. 4, is very useful where the desired controller may be a device that is impractical to use or one that uses very complicated algorithms to calculate the control signal.
- Identifying the system inverse (23,24). Figure 5 shows how a neural network can be used to identify the inverse of a plant. This approach, of course, requires that an inverse of the plant be feasible.
- Differentiating a model. The application of this idea requires that a plant model be available in a form that can be differentiated. The plant model is in the form of a layered network. This approach is illustrated in Fig. 6 and will be discussed in more detail later.

Some drawbacks to the use of conventional ANNs follow:

- It is difficult for an outside observer to understand or modify the network decision making process.
- Conventional ANNs may require a long training time to get the desired performance.
- Although a number of applications of ANN-based controllers as PSSs have been reported in this article, most of these are the supervised learning algorithms that require a desired controller as reference for training purposes.
- The selection of the number of neurons and the number of layers in multilayer networks is not a trivial task. It is, to a large extent, a process of trial and error.

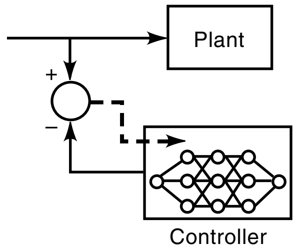

Figure 5. Inverse plant modeling using a network.

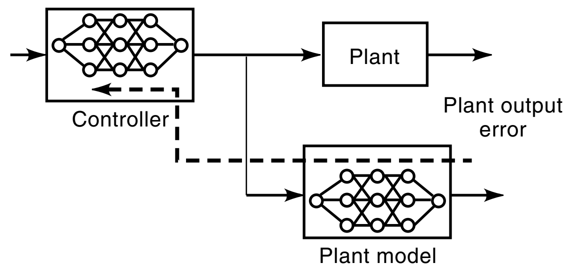

Figure 6. Backpropagating through a forward model of the plant.

ADAPTIVE CONTROLLERS

The adaptive control theory provides a possible way to solve many of the problems associated with the CPSS. Two distinct approaches—direct adaptive control and indirect adaptive control—can be used to control a plant adaptively. In the direct control, the parameters of the controller are directly adjusted to reduce some norm of the output error. In the indirect control, the parameters of the plant are estimated as the elements of a vector at any instant k, and the parameters vector of the controller is adapted based on the estimated plant parameter vector. At each sampling instant, the input and output of the generating unit are sampled, and a plant model is obtained by some on-line identification algorithm to represent the dynamic behavior of the generating unit at that instant in time. It is expected that the model obtained at each sampling instant can track the system operating conditions. The required control signal for the generating unit is computed based on the identified model. Various control techniques can be used to compute the control. All control algorithms assume that the identified model is the true mathematical description of the controlled system.

Mathematical-Algorithm-Based Adaptive PSS

In this case, sampled data design techniques are used to compute control in the following way:

- Select a sampling frequency f, about ten times the normal frequency of oscillation to be damped.
- At each sampling interval ($T = 1/f$), update the system model parameters. A number of identification algorithms have been developed using the discrete domain mathematics. Least squares or extended least squares technique, in recursive form, are usually used to identify the system (i.e., the discrete transfer function of the controlled plant).
- Use the updated estimates of the parameters to compute the control based on the control strategy chosen. Various control strategies, among them the minimum variance, pole-zero assignment pole assignment, pole shift have been proposed.

Extensive amount of work has been done to develop and implement a pole-shift-based adaptive PSS as reported in Refs. 25–28. Such a PSS can adjust its parameters on-line according to the environment in which it works and can provide good damping over a wide range of operating conditions of the power system. To keep the sampling period small enough for on-line control, there must be a compromise between the order of the identified model and the computation time for parameter identification and optimization. Thus the identified model is generally a low-order discrete model. Because the power system is a high-order nonlinear continuous system, care must be taken to ensure that the low-order discrete identified model can properly describe the dynamic behavior of the power system. Thus, there must be a compromise between the order of the discrete model and the computation time for parameter identification and optimization. With the present high-speed microprocessors, this is not a large constraint.

Adaptive Neural-Network-Based PSS

The success of ANNs to control unknown systems under significant uncertainties makes them very attractive. Using the on-line learning features of neural networks, the time-varying power plant can be tracked, and the control signal can be computed accordingly. Because of their inherent features, ANNs do appear to be able to implement many functions essential to control systems with a high degree of autonomy (29). Identification of the power plant model using an on-line recursive identification technique is a computationally extensive task. Neural networks offer the alternative of a model-free method. An ANN-based controller using indirect adaptive control method has been developed. It combines the advantages of neural networks with the good performance of the adaptive control. This controller employs the learning ability of neural networks in adaptation process and is trained in each sampling period. The controller consists of two subnetworks. The first one is an adaptive neuroidentifier (ANI), which identifies the power plant in terms of its internal weights and predicts the dynamic characteristics of the plant. The identifier is based on the inputs and outputs of the plant and does not need the states of the plant. The second subnetwork is an adaptive neurocontroller (ANC), which provides the necessary control action to damp the oscillations of the power plant.

The success of the control algorithm depends upon the accuracy of the identifier in tracking the dynamic plant. For this reason, the ANI is initially trained off-line before being hooked up in the final configuration. The training is performed over a wide range of operating conditions and a wide spectrum of possible disturbances for the generating unit. After the off-line training stage, the ANI is hooked up in the system. Further training of the ANI and ANC is done on-line every sampling period. On-line training enables the controller to track the plant variations as they occur and to provide a control signal accordingly. It also considers the nonlinear nature of the plant. Two versions of this controller have been developed and studied.

- *Multilayer-network-based controller* (30). In this case, the feedforward multilayer network is employed in each of the two subnetworks to build the adaptive neural network PSS. It is trained in each sampling period using an on-line version (31) of the back-propagation algorithm. The errors used to train the ANI and ANC are both scalar, and the learning is done only once in each sampling period for each of the two subnetworks. This simplifies the training algorithm in terms of computation time.
- *Recurrent-network-based controller* (32). In this case, a recurrent network is employed in each of the two subnetworks to build the adaptive neural network. The main difference with respect to the feedforward network is that a recurrent network has at least one feedback loop. Feedback has a profound impact on the learning ability of the network and on its performance. The feedback loop involves the use of a unit delay element, which results in a nonlinear dynamic behavior of the network. In all other respects, the two versions are similar. The errors used in training are scalar, and the learning is done only once in each sampling period for each of the two subnetworks.

Adaptive-Fuzzy-Logic-Based PSS

Obtaining the rules for a fuzzy logic controller, known as knowledge elicitation, is a major bottleneck in the development of FLC. This can be overcome by using adaptive fuzzy systems, which automatically find an appropriate set of rules and membership functions (33,34). An adaptive fuzzy system is implemented in the framework of an adaptive network structure and equipped with a training (adaptation) algorithm. The architecture of the adaptive fuzzy controller is shown in Fig. 7.

Training data are presented to the network, and the network computes its output. Error between the system output and the desired output is back-propagated through the whole network to adjust the network parameters such that the output error is reduced at each step. Similar to ANN, there are different approaches to train an adaptive fuzzy controller.

The most straightforward approach is to train the controller using another desired controller (35). To avoid the use of another controller for training, a self-learning approach (36) can be used to train an adaptive fuzzy controller. In this approach, a separate adaptive fuzzy identifier is trained to behave like the plant. Thus a self-learning adaptive fuzzy logic controller has two adaptive fuzzy systems, one acting as the controller and the other acting as the plant identifier (37). This identification is similar to plant identification in the mathematical-algorithm-based adaptive controller, except that the plant identification is done by an adaptive fuzzy system capable of modeling nonlinearities. The utility of the

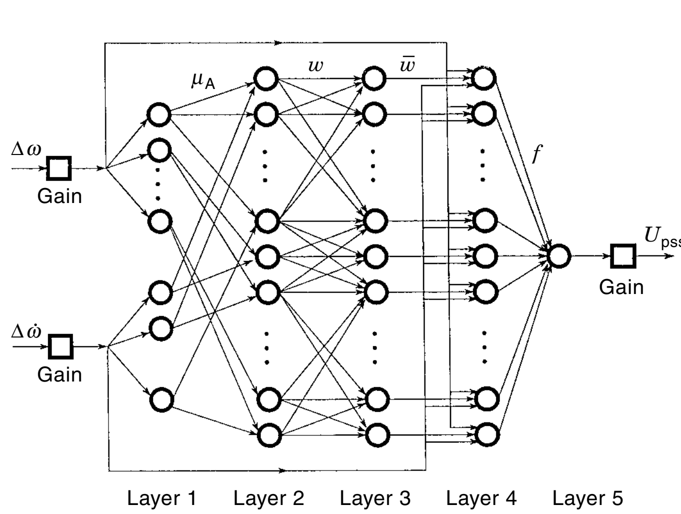

Figure 7. Architecture of ANF PSS.

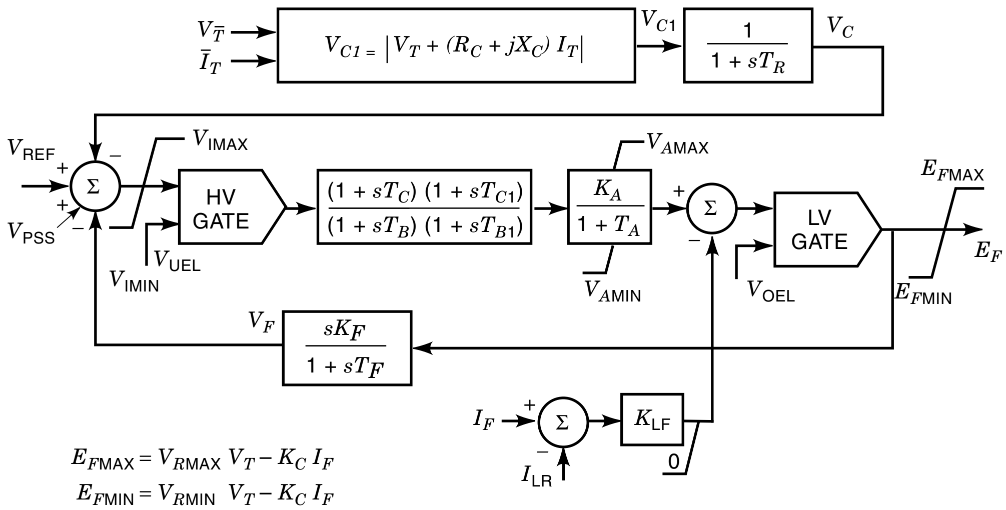

Figure 8. AVR and exciter model Type ST1A, IEEE standard P421.5,1992.

plant identification is that it can compute the derivative of the plant's output with respect to the plant's input by means of the back-propagation process. The final output error of the plant is back-propagated through the adaptive fuzzy identifier to obtain the equivalent error for the controller output. This is then back-propagated through the adaptive fuzzy controller that uses it to learn the control rule.

Although adaptive fuzzy systems offer the potential solution to the knowledge elicitation problem, they still suffer from the problem of setting the structure of the fuzzy system in advance. The structure, expressed in terms of the number of membership functions and the number of inference rules, is usually derived by trial and error. When the number of inference rules is small, the inference rules cannot describe the input/output relationship of given data precisely. On the contrary, when the number of inference rules is large, the generalization capability of the inference rules is sacrificed because of the overfitting problem. Therefore, the number of inference rules must be determined from the standpoint of overall learning capability and generalization capability. This problem can be resolved by employing a genetic algorithm to determine the structure of the adaptive fuzzy controller (38). By employing both genetic algorithm and adaptive fuzzy controller, the inference rules parameters of the inference rules can be tuned, and the number of membership functions can be optimized at the same time. This optimization contains two major processes:

- Search for the optimum number of rules and shape of membership functions by using genetic algorithm.
- Train the network to determine the consequent parts of the rule base by the gradient descent algorithm.

CONCLUDING REMARKS

Power system stabilizers based on all control algorithms described previously have been studied extensively in simulation on a single-machine infinite-bus system and on a multimachine system. They have also been implemented and tested in real-time on a physical model of a single-machine infinite-bus system in the laboratory with very encouraging results. The mathematical-algorithm-based adaptive PSS has also been tested on a multimachine physical model (39) and on a 400 MW thermal machine under fully loaded conditions connected to the system (40). These studies have shown quite clearly the advantages of the advanced control techniques and intelligent systems.

APPENDIX

The generating unit is modeled by the following seven first-order differential equations:

$$\dot{\delta} = \omega_0 \omega \tag{2}$$

$$\dot{\omega} = \frac{1}{2H}(T_m + g + K_d \dot{\delta} - T_e) \tag{3}$$

$$\dot{\lambda}_d = e_d + r_a i_d + \omega_0(\omega + 1)\lambda_q \tag{4}$$

$$\dot{\lambda}_q = e_q + r_a i_q + \omega_0(\omega + 1)\lambda_d \tag{5}$$

$$\dot{\lambda}_f = e_f - r_f i_f \tag{6}$$

$$\dot{\lambda}_{kd} = -r_{kd} i_{kd} \tag{7}$$

$$\dot{\lambda}_{kq} = -r_{kq} i_{kq} \tag{8}$$

An AVR and exciter model from the IEEE standard P421.5,1992, Type ST1A is shown in Fig. 8.

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EXPECTED VALUE. See Probability.

EXPERIMENTS IN RELIABILITY. See Reliability via designed experiments.