CHAPTER 1

INTRODUCTION

This chapter presents an introduction to the problem of power system stability and its control. Basic concepts, classification and definition of related terms used in power system stability analysis are described. A review of three categories of control strategies for synchronous generator control is conducted. They include conventional power system stabilizer(PSS) control, adaptive PSS control and intelligent control systems. The objectives of the thesis are then summarized. Finally an outline of the thesis is presented.

1.1 POWER SYSTEM STABILITY

An electric power system consists of a large number of generators, transmission lines, and various loads. It is characterized by dynamic phenomena of which stability and control are dominant. To maintain a successful operation of a power system, there are three functional requirements that must be satisfied simultaneously, namely, service continuity, voltage and frequency stability, and economic efficiency. Of these three requirements, system stability and control is of primary importance.

Synchronous generators connected through a transmission network must run in parallel, that is, at the same instantaneous speed. Automatic control systems are installed to keep the rotating speed difference among the generators within narrow bounds. If any one generator runs faster than another, the angular position of its rotor relative to that of the slower generator will continue to advance as long as the speed difference exists, and its generated voltage will likewise advance in phase relative to the voltage of the slower machine. The resultant phase difference shifts a load from the slower machine to the faster machine, tending to reduce the speed difference.

This shifting process is a nonlinear function of the difference in rotor angles. When this difference in rotor angles exceeds a upper limit, load shifting reverses and speed difference increases instead. This is referred as the loss–of–synchronism phenomena. Loss of synchronism can occur between one machine and the rest of the system or between groups of machines. Power system stability may take different forms, depending on the state of the system. During fault conditions, the major concern is whether the system can stay interconnected. The loss of interconnection will only increase instability. On the other hand, during normal operation, the task is to keep voltage and frequency fluctuation within an acceptable error.

Power system stability can be classified into short–term and long–term stability. The former can be further categorized by steady–state stability and transient stability. Steady–state stability is the stability following a small disturbance for which the equations that describe the dynamics of the system can be linearized for the purpose of analysis. A system is said to be steady–state stable for a particular operating condition, following a small disturbance, if the system can reach another steady–state condition that may or may not be identical or close to the pre–disturbance operating condition of the power system. A system is said to be transient stable for a particular operating condition and for a specified large disturbance if, following that disturbance, it can reach an acceptable steady state operating condition[1–1].

Load plays an important role in system stability. Lightly loaded power transmission lines force leading power factors on generators, making them more unstable. Steam and diesel plants can only reduce their loads to about 50% full load; below that, they begin to shut down. Daily start up and shutdown cycles create tremendous thermal stress and reduce the useful life, especially of steam plants[1–1]. On the other hand, heavy loads require huge amounts of spinning reserve to meet possible plant outages. For this reason, interconnected tie lines should never trip on overload. They may stay connected to their thermal limits.

In a given system, load or demand is the major independent variable that initiates changes. Everything else in the system is designed to meet the demand with reliability, quality and economy. When demand changes, corresponding changes in frequency and voltage occur. As the equipment in a system is designed to operate at a certain voltage and frequency, these two quantities must be controlled when the above said changes occur. This is why there are always controllers even on old power equipment.

As our society's consumption of electrical energy has increased steadily, power systems over large geographic areas have been interconnected to meet this demand and to provide a reliable electrical power service. At the same time, sophisticated control equipment and protection schemes have been added to power systems to enhance its stability. As a result the analysis of power system stability has become more difficult. Fortunately, advanced mathematical modeling and better computation facilities have made it possible to solve the complicated problem of stability investigations. In this thesis, the focus is placed on short–term stability studies, using artificial neural networks(ANNs) and fuzzy logic(FL) theory.

Synchronous generators are to supply sufficient electric energy to meet the demand in the system. The objective of generator control is to maintain the terminal voltage and frequency at some predetermined values. This is accomplished by two principal control loops, one for frequency control and the other for voltage control. In long–term stability, frequency control is accomplished by a speed–governor through a turbine that drives the generator; voltage control is accomplished by a voltage regulator through an excitation system that provides the bridge for converting mechanical power into electrical power in the generator.

In short–term stability, i.e., transient stability, the working mechanism of the control is different. As transient stability accounts for only several seconds following the disturbance, the speed–governing and turbine system is not capable of following the changes the system is experiencing. For practical reasons it is detrimental to the equipment to open and close the steam valve so often and so fast when the transient is oscillatory. In the voltage control loop, as fast–acting excitation systems are used with high gain, when there is a contingency, such as a three–phase to ground fault, the voltage dips. The excitation system will raise the field voltage to the upper ceiling and boost the reactive power of the generator so that the voltage level can be brought back to normal.

At the same time, this fast–acting excitation brings in another problem. For situations with heavy load or weak transmission system, the high gain AVR introduces negative damping. This means that after the first swing in the transient, sustained oscillations can occur. This is harmful because the power transfer over transmission lines has to decrease and the stability integrity of the system is in danger. This was why in the 60's power systems engineers started installing additional controllers called power system stabilizer(PSS) to suppress sustained low frequency oscillations.

1.2 STABILITY OF SYNCHRONOUS GENERATORS

1.2.1 General Concepts

Power system stability is principally concerned with the stability of synchronous generators and tie–line stability in a system. As the load increases, more generators are continuously added to the system. To achieve economic benefits, generators of larger sizes and high reactance have been designed. As a result, more sophisticated control designs are required to provide compensating effects offsetting the reductions in stability margins inherent from such designs. Research on this subject has received great attention since the 70's[1–2]. Over the past three decades, continuing attention has been focused on the effects of excitation control on the damping of oscillations. These supplementary excitation controllers, i.e., power system stabilizers(PSSs), have been added to counteract the effects of high gains of automatic voltage regulators(AVRs). These AVRs usually have high gains and are fast. This way transient system stability can enhanced. An adverse effect of the fast–acting AVRs is a reduction in the damping.

As the size of synchronous generators increases, more spinning reserve is required in the system. To achieve economical operation, local power systems are connected together through tie–lines to reduce the requirement of high spinning reserves. This practice has given rise to another problem that is apart from local oscillations. It is possible that inter–area oscillations can occur following certain disturbances in certain geographical areas.

1.2.2 Conventional PSS control

Excitation control can increase the stability limits of synchronous generators. Exciters need to have a high gain to perform this function. To achieve a high

DC gain and a low transient gain at the same time, a series compensation circuit can be used.

When a system exhibits negative damping characteristics, the voltage regulator usually aggravates the situation by increasing the negative damping. Great success has been achieved in reducing inter–area oscillations by using power system stabilizers to bring positive damping to the system. Supplementary signals are introduced through a compensation network to the excitation summation conjunction. This network provides the proper phase compensation so that the positive torque generated will be in phase with the change of speed of the machine.

Since the network transfer function changes when there is a change in system loading and/or network topology resulted from line switching or transmission fault, it is up to the designer to choose one situation where the parameters of the compensation network are tuned. In this section, the design of PSSs belonging to this category is reviewed.

There are many tuning strategies for determining the parameters of a conventional PSS. These tuning methods can be classified into the following categories, i. e., (1) classical control theory;(2) modern control theory; and (3) unclassified methodologies. The following review is presented according to this classification.

In 1975, Laha and Bollinger [1–3] proposed a PSS design procedure based on pole–placement. First, the frequency response is obtained by

Fourier analysis of wide bandwidth excitation signals. Then, the transfer function of the generator is derived by fitting a straight–line approximation to this frequency response. Finally the state–space model of the generator is obtained from this transfer function. In order to obtain the desired response, the closed–loop poles are placed using a PSS compensation network. The paper concludes that a PSS designed as such can damp the local oscillatory mode of the generator for the loading conditions at which the frequency response is obtained. In the same year, Bollinger et al [1–4] described a design method based on root locus techniques. In this algorithm, the open–loop poles and zeros of the generator are determined from the frequency response between the voltage regulator input and the electric power output of the generator. In [1–5], Bollinger and Lalonde designed a PSS compensation network to move a lightly–damped local mode to the left of the s–plane. To damp power oscillations on a tie–line between two large power pools, Bollinger, Winsor and Campbell [1–6] used a phase–compensation tuning technique to design a PSS based on frequency response data obtained by applying wide–bandwidth noise signals to the generator. In [1–7], Bollinger and Mistr designed a PSS for a pumped storage plant, using frequency response measurements and the root locus method.

There is a huge collection of papers on PSS design using eigenanalysis. De Mello et al [1–8] and others [1–9]~[1–13] have provided basic theory and practical applications of their techniques.

Modern control theory has been used to design optimal controllers. In 1972, Yu and Moussa proposed optimal PSS designs[1–14,1–15]. Later on others proposed designs in the same category[1–16]~[1–18]. The problem with optimal control design is that the performance of the designed controller will deteriorate dramatically when the operating condition moves away from the point at which the controller was designed.

There are two basic papers on the application of conventional PSS. In 1974, de Mello and Concordia[1–2] presented the fundamental concepts of using supplementary excitation control to stabilize a synchronous generator. Using a one–machine infinite–bus system as the study system, the authors presented a complete design procedure to synthesize a PSS compensation network for generator stabilization. In 1981, Larsen and Swann presented three papers [1–19] on applying conventional power system stabilizers. These papers serve as both a survey and a tutorial.

1.2.3 Adaptive PSS Control

In the 1970s and early 1980s, adaptive control research progressed dramatically in two directions, i.e., self–tuning control and model reference control. At the same time, the availability of ever–increasing computing power made it possible to realize real–time on–line control, allowing relatively complex recursive identification algorithms to modify control actions in response to new system states.

The goal of adaptive control is to make the process under control less sensitive to changes in process parameters and the unmodeled process dynamics. Adaptive controllers attempt to sense the changes of the dynamic process and make on–line adjustments to control parameters and strategies. There are two categories of adaptive control approaches, i.e., self–tuning control(STC) and model reference adaptive control(MRAC). With self–tuning control, system parameters are identified on–line using parameter identification schedules such as recursive least squares(RLS). Then the estimated parameters are utilized in the control strategy to modify control parameters. With model reference adaptive control, the output of the controlled process is compared with that of a reference model that exhibits the desired response. The error is used to modify controller parameters, with the objective of having the process output converge to the output of the reference model.

This is useful in control applications of power systems. With loads, generation schedules and network topology changing over time, the operating point of a power system changes. Fixed–parameter controllers designed for a specific operating condition can't maintain the same quality of performance at other operating points. There are a number of publications on this subject. A majority of the published works used self–tuning control schemes[1–20]~[1–26]. An MRAC scheme is used in [1–27]. They were mainly concerned with excitation control and load–frequency control.

1.2.4 Intelligent Control Systems

(1) *Promises of Artificial Intelligent Control*

Successful control of synchronous generators in a power system plays an important role in maintaining its continuous operation and integrity. Classical and modern control techniques using mathematical system theory, which deals with the analysis and synthesis of dynamical systems such as power systems, have performed remarkably well. However these classical techniques are inadequate when one is confronted with the control of complex systems characterized by poor models, high dimensionality of the decision space, multiple performance criteria, drifting parameter values, disturbances, failing component parts and nonlinearalities. These difficulties can be classified into three categories, namely, complexity in computation, nonlinearity with many degrees of freedom, and uncertainty. As the system to be controlled becomes more complex, so does the complexity associated with the computation of the control law and the task of implementing the control in a timely fashion. An intelligent control system is one that can sense the environmental changes, process the sensor data, generate and execute a timely control action that guides the system from an initial state to a terminal state satisfying the various constraints and objectives imposed. The greater the ability to successfully deal with the above said difficulties, the better the control system is.

Intelligent control, which is defined as a combination of control theory, operations research and artificial intelligence(AI) is emerging as one of the most popular new technologies in the industrial and manufacturing worlds. The assumption that all control engineering analysis and design can be reduced to the solution of a set of deterministic algebraic and differential equations has been challenged by these technologies. The data for plant modeling , measuring and controlling are rarely exact. Therefore the degree of uncertainty introduced in the modeling and controlling process becomes an important factor in influencing system performance. This is the driving force behind much of control engineering research.

Among the many possible new techniques based on AI, fuzzy logic is now the most visible and productive area. Since the first fuzzy chip in 1987, there have been 2000 patents issued in Japan. A majority of the patents issued in the US are from Japan on fuzzy logic controlled products, such as washing machines, air conditioners, camcorders, automobiles, subway trains and mobile robots. More recently, neural network theory has emerged as a complementary technique to fuzzy logic rather than competitive. Neural networks (a) are adaptive – they can learn from examples and then infer solutions from data presented to them; (b) can generalize – they can handle incomplete or imperfect data providing a measure of fault tolerance; (c) are non–linear and (d) are highly parallel. Motivated by the power of the human brain in parallel information processing, researchers have been exploring the applicability of artificial neural networks(ANN) similar to a nervous system architecture to solve highly complex non–linear problems.

While fuzzy logic aims at exploiting the tolerance for imprecision and uncertainty to achieve tractability, robustness and low solution cost, neural networks mimic human beings to learn from examples. In contrast to fuzzy logic, where the knowledge is expressed explicitly, neural networks accommodate by coding it among the connecting weights of the network. Neural networks have no logical structure behind them.

In summary, fuzzy logic is good at various aspects of uncertainty–knowledge representation, but not powerful enough to carry out learning and adaptation to a changing environment, while neural networks are efficient structures capable of learning from examples, but they're purely numerical constructs. The learning of such a network is accomplished at the numerical level, and does not contribute towards developing new schemes of knowledge representation. Because of the uncertainty and complexity of the power system, the control of a synchronous generator is a good example where the combination of neural networks and fuzzy logic as a control system can challenge the classic design of control. The reason is that such an intelligent controller can provide robust control over the entire operating zone of the generator. In contrast, the performance of classic controllers deteriorates when saturation takes place or other nonlinearities come into play. There is evident interest in combining both fuzzy logic and neural networks for power system control.

(2) *ANN Control*

Motivated by the power of the human brain in parallel information processing, researchers have been exploring the applicability of artificial neural networks (ANN) similar to nervous system architecture to solve highly complex nonlinear problems. It is reported[1–28] that generalized neural networks containing multilayer neural networks and linear dynamical systems 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 control systems for any dynamic system of varying complexity, thanks to the high capability of parallel information processing of the neural networks.

Unlike neural networks used in cognitive processing, those used in control systems are intentionally designed and trained in an environment in which the neural networks and the plant to be controlled are placed in a closed loop. That is, using neural networks to control a dynamic system requires that the neural networks be trained on–line. The specific training methods to be employed depends on the arrangement of the neurocontroller in the control loop. There are five generic approaches to designing a neurocontroller. They are supervised control including CMAC(Cerebellar

Model Arithmetic Computer), direct inverse control, neural adaptive control, backpropagation of utility, and adaptive critic.

In supervised control, a neural net learns the mapping from sensor inputs to desired actions by adapting to a training set of examples of what it should have done, i.e. it learns to imitate a human or a computer program which already knows how to perform the task. The CMAC approach seems to hold promise in on–line learning where classical backpropagation shows poor performance because of its slow learning. This method has found applications in function approximation, pattern recognition and robotic control[1–29].

In direct inverse control, a neural net learns the inverse dynamics of the plant to be controlled. That is, the network receives the desired system trajectory as an input and produces the correct control action. A major problem with inverse control arises when many plant inputs produce the same output, i.e. when the plant's inverse is not well defined. In this case, the neural network will attempt to map the same input to many different target responses. In both supervised control and direct inverse control, there is no planning or optimization. In neural adaptive control, linear mappings used in standard designs such as MRAC(Model Reference Adaptive Control) are replaced by neural nets, resulting in greater robustness and ability to handle nonlinearity.

The backpropagation of utility adapts an optimal controller essentially by solving a calculus of variations problems. That is to develop a schedule of actions so as to maximize utility over a period of time. The emphasis is placed on performance over a period of time rather than instantaneous performance. As with the calculus of variations, this method requires a model of the system to be controlled (which may itself be a neural net) and does not allow for noise.

The adaptive critic approach can be thought of as either a generalization of backpropagation of utility or a generalization of reinforcement learning. It does not require a model of the system. The underlying idea is to approximate the Bellman equation of dynamic programming. Reinforcement learning is a very general approach to learning that can be applied when the knowledge required to use supervised learning is not available. It basically involves two problems. The first one is to construct a critic capable of evaluating plant performance in a way that is both appropriate to the actual control objective and informative enough to allow learning. The second problem is to determine how to alter controller outputs to improve performance as measured by the critic.

In the past decade, the field of neural networks has grown from a mere handful of researchers to thousands spread throughout the academic and industrial world. Applications have been developed in domains as varied as character recognition, pattern classification, dynamic system control, and stock market prediction. Specifically, as applied to power system engineering[1–30], neural networks have found their applications in areas such as nuclear power generation, system operation, modeling and prediction, control, load forecasting, scheduling and optimization, and fault diagnosis. Many of these problems have solutions in normal logic and analytical methods. With the use of neural networks(NNs), there seems to be simpler and faster methods of solving these problems. On the other hand, there seems to have been a big gap between research and implementation of these research results in utilities, especially those related to safety systems.

(3) *FL Control*

Since the first paper on fuzzy sets was published in 1965 by Lotfi A. Zadeh[1–31], applications of fuzzy theory have penetrated not only in the fields of soft sciences such as biological and social sciences, linguistics, psychology and economics, but also in those fields where dependencies of variables are well–defined. This latter category of applications is advantageous as precision is illusory in the real world. Fuzzy algorithms possess a remarkable innate ability to exploit the tolerance for imprecision to achieve tractability, robustness and low cost solution. In contrast, traditional control techniques fail to do so when using precise algorithms to arrive at a solution.

Fuzzy control has found successful applications in industrial processes such as the Automatic Train Operation(ATO) at Sandai, as well as electronic consumer products such as washing machines, vacuum cleaners. Today, we are experiencing the turning point, i.e., a paradigm shift from traditional hard computing to soft computing. The latter is mainly involved with fuzzy logic(FL), artificial neural network theory(ANN), and probabilistic reasoning(PR). FL is concerned with imprecision and approximate reasoning; ANN with learning, generalization and error tolerance; and PR with uncertainty and propagation of belief.

One important characteristic of an intelligent control system is that it has the ability to control a system in uncertainty or unknown environments. Fuzzy set theory provides a systematic framework for dealing with different types of uncertainty within a single conceptual framework. This is why fuzzy inference procedures are crucial to the process of managing uncertainty.

(4) *Literature Review*

The application of neural networks to the control of synchronous machines is at a very early stage. The control problem may concern any of the following three subsystems, i.e., the prime–mover frequency control, excitation terminal voltage control and low frequency oscillation control which involves coupling among machines connected through transmission lines. Several control schemes in this area have been published.

A nonlinear adaptive controller based on neural networks has been proposed very recently for control of synchronous generators[1–32]. The control system consists of an identifier and a controller. The connection weights of the neural networks are adjusted adaptively so as to respond to changes of operating conditions. Digital simulations of the control scheme have been carried out for a one–machine infinite bus system. In [1–33], an artificial neural network (ANN), functioning as a power system stabilizer (PSS), has been used to map the inverse dynamics of the controlled plant, 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. In [1–34] an adaptive forced–action automatic excitation controller for a salient–pole synchronous generator has been proposed based on an ANN which is trained using input–output patterns. The backpropagation algorithm was chosen for training the ANN.

A neurocontroller for load frequency control has been proposed in [1–35] in which a feedforward neural network is trained to control the steam admission value of the turbine that drives the generator, thereby restoring the frequency to its nominal value. Different from conventional integral control which is slow, the proposed neurocontroller uses an estimator (which may itself be neural net) to account for load perturbation in driving the plant controller. In [1–36], on the basis of a cluster–wise segmented associative memory system, real–time adaptation of a neurocontroller for a power system is carried out using an error–based on–line learning scheme. The capability of self–organization and predictive estimation of neural net computers has been utilized in the design. In [1–37], an on–line trained neurocontroller has been proposed for turbogenerators based on a hierarchical architecture of neural networks. A nonlinear adaptive controller based on neural networks has been proposed very recently for control of a synchronous generator[1–38]. The control system consists of an identifier, a controller and a reference model. The connection weights of the neural networks are adaptively adjusted so as to respond to changes of operating conditions. Digital simulations of the control scheme have been carried out for a multi–machine power system.

Other subjects that have drawn much attention are DC motor and induction motor controls due to their simpler dynamics. Reported methodologies can be broadly divided into two categories; one is to model the existing controller by an ANN and replace that controller with the trained neurocontroller; the other to identify the dynamics of the motor system on–line using an ANN and then construct a control strategy using the updated ANN weights.

Several intelligent control schemes have been proposed in the last few years, based either on neural networks or fuzzy logic for either voltage control or system stability control. Their hardware implementations have not been widely reported. Only has Mitsubishi filed its patent in the US for a fuzzy logic power system stabilizer(PSS). In this section, representative papers are reviewed. A PID type fuzzy logic PSS is proposed by Hiyama[1–39,1–40]. The controller uses real power of the generator as input. After integrating the input signal twice, acceleration, speed and phase signals are derived which are used as the inputs to a fuzzy logic controller. The output is the control signal to the excitation loop which is supposed to provide a damping torque in phase with the change of speed. There are three to five parameters to be tuned on site if such a PSS is to be installed. Tuning parameters of the design on site is always a disadvantage, just as for conventional PSSs.

An automatic voltage regulator is designed for a synchronous generator, based on fuzzy logic control[1–41]. Its task is to maintain the terminal voltage of the generator constant. It is not concerned with transient stability. A self–organizing fuzzy controller is proposed to improve transient stability of a multimachine system through additive real power control which may be implemented by a braking resistor, fast valving or superconducting magnetic storage unit[1–42]. The controller is equivalent to an expert system to evaluate the right amount of accelerating energy to be shed in order to stabilize the generator. The potential of the excitation system is not exhausted as the control signal does not go to this channel, unless there is another power system stabilizer.

1.3 Statement of Objectives

The goal of this research is to develop an intelligent controller that is robust to changing environment and inexpensive to implement. The control of a synchronous generator in a power system is different from controlling most other industrial processes in that the dynamic of one generator is affected by that of all other generators, loads, topologies of the transmission network as well as types of disturbances. It would be too expensive, too complicated and impractical to have all this information fed back to the controller to arrive at an optimum control strategy.

For example, to improve transient stability through excitation control, the key point is to provide a damping torque in phase with the change of speed to the generator. In practice, this is achieved by using a conventional power system stabilizer(CPSS) which is nothing but a phase lead–lag compensation circuit. When the operating point of the system changes, the parameter–fixed compensation circuit may not provide adequate phase compensation anymore. Therefore, the controller may not perform as desired. This is why researchers have been looking for better designs based on AI techniques.

Intelligent controllers will be designed based on a technique that combines the purely numerical approach of neural networks and the structured–knowledge representation of fuzzy logic. The functions of the neural networks will be limited to state estimation and pattern recognition. The architecture of the entire control system remains fuzzy. Specifically, this thesis aims at (1)investigating the possibilities of using advanced control theory for power system stability control, (2)designing advanced intelligent control systems for synchronous generator control in a multi–machine environment, (3)developing an advanced simulation environment for power system transient stability studies. The following tasks were carried out to achieve the stated objectives.

- Review of literature pertaining to power system stability and control using conventional and adaptive control theory; presentation of a combined theory of neural networks and fuzzy logic.
- Improvement of the Transient Stability Simulation Package(TSSP)[1–43] implemented in SIMULINK environment. Addition of new features and functions for extended transient stability studies.
- Design and performance studies of an ANN–FL(artificial neural network and fuzzy logic) controller as applied to the speed–tracking control of a DC motor.
- Design and performance evaluation of two ANN–FL PSSs for a multi–machine power system. Simulated results are compared with those obtained using a conventional PSS.

1.4 OUTLINE OF THE THESIS

The research reported in this thesis has been focused on developing advanced intelligent control systems for stability control of power system synchronous generators.

A review of stability and control problems in a large power system is conducted in Chapter 1. Due to the interconnection of local power systems into large power pools, stability problems appeared. Negative damping introduced by high gain fast–acting AVRs and weak inter–ties between pools resulted in lightly damped oscillations.

Artificial neural networks (ANNs) and fuzzy–logic(FL) can be used to model complex dynamic systems. Basic concepts, definitions of related terms used in ANNs and FL are given in Chapters 2 and 3. A feedforward ANN architecture and the four types of fuzzy reasoning methods are described. Combining the merits of ANNs and FL, an hybrid modeling methodology is proposed in Chapter 4.

Utilizing the hybrid modeling technique, Chapter 5 designs an intelligent controller for speed–tracking control of a DC motor. Comparison of transient responses of the system under different disturbances are performed using a PID controller and the newly–designed ANN–FL controller. Conclusions are drawn from the simulation studies.

Modeling aspects of composite power systems are dealt with in Chapter 6. Mathematical representations of various power components, including synchronous generators, induction motors, high voltage AC/DC transmission networks, are given. Block diagrams of excitation control systems, speed–governing and turbine systems as well as power system stabilizers are presented.

A computer software for transient stability simulation studies of a power system is developed in Chapter 7 in SIMULINK environment. The

Transient Stability Simulation Package (TSSP) [1−43] is realized using basic SIMULINK blocks and MATLAB functions. Basic instructions on how to build a simulation model of a power system are given.

The hybrid ANN−FL modeling technique is applied to a two−machine infinite−bus power system in Chapter 8. Based on experience gained in Chapter 5, two ANN−FL power system stabilizers, one using speed deviation as input, the other using accelerating power, are designed. Their performance evaluation is carried out by simulation studies.

Chapter 9 concludes this thesis.