Chapter 1

Introduction

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Zadeh is credited with introducing the concept of fuzzy sets in 1965 as a mathematical means of describing vagueness in linguistics. The idea may be considered as a generalization of classical set theory. In the decade since Zadeh's pioneering paper on fuzzy sets [1], many theoretical developments in fuzzy logic took place in the United States, Europe, and Japan. From the mid-1970s to the present, however, Japanese researchers have done an excellent job of advancing the practical implementation of the theory; they have been a primary force in commercializing this technology. Much of the success of the new products associated with the fuzzy technology is due to fuzzy logic, and some is also due to the advanced sensors used in these products.

1.1. FUZZY SETS

The basic idea of fuzzy sets is quite simple. In a conventional (nonfuzzy, hard, or crisp) set, an element of the universe either belongs to or does not belong to the set. That is, the membership of an element is crisp—it is either yes (in the set) or no (not in the set).

A fuzzy set is a generalization of an ordinary set in that it allows the degree of membership for each element to range over the unit interval [0, 1]. Thus, the membership function of a fuzzy set maps each element of the universe of discourse to its range space, which, in most cases, is assumed to be the unit interval.

One major difference between crisp and fuzzy sets is that crisp sets always have unique membership functions, whereas every fuzzy set has an infinite number of membership functions that may represent it. This enables fuzzy systems to be adjusted for maximum utility in a given situation.

1.2. FUZZY SYSTEMS, COMPLEXITY, AND AMBIGUITY

Zadeh's principle of incompatibility was given in 1973 to explain why there is a need for a fuzzy system theory. The principle states, in essence, that as the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics. This suggests that complexity and ambiguity (imprecision) are correlated: "The closer one looks at a real-world problem, the fuzzier becomes its solution" [2].

It is a characteristic of the way humans think to treat problems involving complexity and ambiguity in a subjective manner. Complexity generally stems from uncertainty in the form of ambiguity; these are features of most social, technical, and economic situations experienced on a daily basis. In considering a complex system, humans reason approximately about its behavior (a capability that computers do not have) and thus maintain only a generic understanding of the problem. This generality and ambiguity are adequate for a human to perceive and understand complex systems.

As one learns more and more about a system, its complexity decreases and understanding increases. As complexity decreases, the precision afforded by computational methods becomes more useful in modeling the system. For less complex systems, thus involving little uncertainty, closed-form mathematical expressions offer precise descriptions of the systems' behavior. For systems that are slightly more complex but for which significant data exist, model-free methods, such as computational neural networks, provide powerful and effective means to reduce some uncertainty through learning based on patterns in the available data.

There are virtually no problems for which we can say that the information content is known absolutely, that is, with no ignorance, no vagueness, no imprecision, no element of chance. Uncertain information can take on many different forms. There is uncertainty that arises because of complexity, for example, the complexity in the reliability evaluation of an electric distribution system. There is uncertainty that arises from ignorance, from chance, from various classes of randomness, from imprecision, from the inability to perform adequate measurements, from lack of knowledge, or from vagueness, like the fuzziness inherent in our natural language.

The nature of uncertainty in a system is an important consideration that the analyst should study prior to selecting an appropriate method to express the uncertainty. For most complex systems where few numerical data exist and where only ambiguous or imprecise information may be available, fuzzy reasoning offers a way to understand system behavior by allowing one to interpolate approximately between observed input and output situations. The imprecision in fuzzy models is generally quite high.

Fuzzy logic is based on the way the brain deals with inexact information. Fuzzy systems combine fuzzy sets with fuzzy rules to produce overall complex nonlinear behavior. Fuzzy systems are structured numerical estimators. They start from highly formalized insights about the structure of categories found in the real world and then express fuzzy if-then rules as some expert knowledge. Being numerical model-free estimators and dynamical systems, fuzzy systems are able to improve the intelligence of systems working in an uncertain, imprecise, and noisy environment.

Some of the information available in developing models of physical processes might be judgmental, perhaps an instinctive reaction on the part of the modeler, rather than hard quantitative information. Fuzzy reasoning allows us to incorporate intuition into a problem.

One prevalent way to convey information is our own means of communication: natural language. By its very nature, natural language is vague and imprecise; yet it is the most powerful form of communication and information exchange among humans. Despite the vagueness in natural language, humans have little trouble understanding one another's concepts and ideas; this understanding is not possible in communications with a computer, which requires extreme precision in its instructions.

To illustrate, consider the interpretation of the term *short-person*. To individual X a short person might be anybody below 5 ft 1 in. To individual Y, a short person is someone who is 5 ft 8 in. or shorter. What sort of meaning does the linguistic descriptor *short* convey to either of these individuals? It is surprising that, despite the potential for misunderstanding, the term short communicates sufficiently similar information to the two individuals, even if they are of considerably different heights themselves, and that understanding and correct communication are possible between them. Individuals X and Y, regardless of their own heights, do not require identical definitions of the term short to communicate effectively. A computer would require a specific height to compare with a preassigned value for "short." The underlying power of fuzzy set theory is that it uses linguistic variables, rather than quantitative variables, to represent imprecise concepts.

Fuzzy systems have been shown to be capable of modeling complex nonlinear processes to arbitrary degrees of accuracy. They have attracted growing interest of researchers in various scientific and engineering areas. The number and variety of applications of fuzzy systems have been increasing, ranging from consumer products and industrial process control to medical instrumentation, information systems, and decision analysis.

1.3. FUZZINESS AND PROBABILITY

Fuzziness is often confused with probability. The newcomer to the field often claims that fuzzy set theory is just another form of probability theory in disguise. Fuzzy set theory provides a means for representing uncertainties. Probability theory has been the primary tool for representing uncertainty in mathematical models. As a result, all uncertainty was assumed to follow the characteristics of random uncertainty.

Basic statistical analysis is founded on probability theory or stationary random processes, whereas most experimental results contain both random (typically noise) and nonrandom processes. One class of random processes or stationary random processes exhibits the following three characteristics:

1. The sample space on which the processes are defined cannot change from one experiment to another, that is, the outcome space cannot change.
2. The frequency of occurrence, or probability, of an event within that sample space is constant and cannot change from trial to trial or experiment to experiment.
3. The outcomes must be repeatable from experiment to experiment. The outcome of one trial does not influence the outcome of a previous or future trial.

However, fuzzy sets are not governed by these characteristics.

The outcomes of any particular realization of a random process are strictly a matter of chance; a prediction of a sequence of events is not possible. For a random process it is only possible given a precise description of its long-run averages.

As can be appreciated, not all uncertainty is random. Some forms of uncertainty are nonrandom and hence not suited to treatment or modeling by probability theory. In fact, one can argue that the predominant amount of uncertainty associated with complex systems is nonrandom in nature. Fuzzy set theory is an excellent tool for modeling the kind of uncertainty associated with vagueness, with imprecision, and/or with a lack of information regarding a particular element of the problem at hand.

The fundamental difference between fuzziness and probability is that fuzziness deals with deterministic plausibility, while probability concerns the likelihood of nondeterministic, stochastic events. Fuzziness is one aspect of uncertainty. It is the ambiguity (vagueness) found in the definition of a concept or the meaning of a term such as *comfortable temperature* or *well cooked.* However, the uncertainty of probability generally relates to the occurrence of phenomena, as symbolized by the concept of randomness. In other words, a statement is probabilistic if it expresses some kind of likelihood or degree of certainty or if it is the outcome of clearly defined but randomly occurring events. For example, the statements "There is a 50-50 chance that he will be there," "It will be sunny tomorrow," and "Roll the dice and get a six" demonstrate the uncertainty of randomness.

Hence, fuzziness and randomness differ in nature; that is, they are different aspects of uncertainty. The former conveys "subjective" human thinking, feelings, or language and the latter indicates an "objective" statistic in the natural sciences.

From the modeling point of view, fuzzy models and statistical models also possess philosophically different kinds of information: Fuzzy memberships represent similarities of objects to imprecisely defined properties, while probabilities convey information about relative frequencies. The quest for a method to quantify nonrandom uncertainty (imprecision, vagueness, fuzziness) in physical processes is the basic premise of fuzzy system theory, for to understand uncertainty in a system is to understand the system itself. As understanding improves, the fidelity in modeling improves.

1.4. WHEN IS A FUZZY FORMULATION APPROPRIATE?

Whenever precision is evident, for example, fuzzy systems are less efficient than more precise algorithms in offering a better understanding of the problem. Requiring precision in engineering models and products translates to requiring high cost and long lead times in production and development. For other than simple systems, expense is proportional to precision: More precision entails higher cost. When considering the use of fuzzy logic for a given problem, an engineer or scientist should ponder the need for exploiting the tolerance for imprecision. Not only does high precision dictate high costs but it also entails low tractability in a problem.

On the other hand, fuzzy systems can focus on modeling problems characterized by imprecise or ambiguous information. The following are situations where it is appropriate to formulate system problems within a fuzzy system framework:

1. In processes involving human interaction (e.g., human descriptive or intuitive thinking)
2. When an expert is available who can specify the rules underlying the system behavior and the fuzzy sets that represent the characteristics of each variable
3. When a mathematical model of the process does not exist, or exists but is too difficult to encode, or is too complex to be evaluated fast enough for real-time operation, or involves too much memory on the designated chip architecture
4. In processes concerned with continuous phenomena (e.g., one or more of the control variables are continuous) that are not easily broken down into discrete segments
5. When high ambient noise levels must be dealt with or it is important to use inexpensive sensors and/or low-precision microcontrollers.

The ability to use fuzzy system tools will allow one to address the vast majority of problems that have the preceding characteristics. Fuzzy formulations can help to achieve tractability, robustness, and lower solution cost.

Any field can be fuzzified and hence generalized by replacing the concept of a crisp set in the target field by the concept of a fuzzy set. Therefore, we can fuzzify some basic fields such as graph theory, arithmetic, and probability theory to develop fuzzy graph theory, fuzzy arithmetic, and fuzzy probability theory, respectively. Moreover, we can also fuzzify some applied fields such as neural networks, pattern recognition, and mathematical programming to obtain fuzzy neural networks, fuzzy pattern recognition, and fuzzy mathematical programming, respectively. The advantages of fuzzification include greater generality, higher expressive power, an enhanced ability to model real-world problems, and a methodology for exploiting the tolerance for imprecision.

1.5. APPLICATIONS OF FUZZY SYSTEMS

Fuzzy systems have superseded conventional technologies in many scientific applications and engineering systems. Fuzzy system techniques are applicable in areas such as control (the most widely applied area), pattern recognition (e.g., image, audio, signal processing), quantitative analysis (e.g., operations research, management), inference (e.g., expert systems for diagnosis, planning, and prediction; natural language processing; intelligent interface; intelligent robots; software engineering), and information retrieval (e.g., databases).

There has been rapid growth in the use of fuzzy logic in a wide variety of consumer products and industrial systems. Notable examples include the following:

1. In electric appliances, for instance, Matsushita builds a fuzzy washing machine that combines smart sensors with fuzzy logic. The sensors detect the color and kind of clothes present and the quantity of grit, and a fuzzy microprocessor selects the most appropriate combination from 600 available combinations of water temperature, detergent amount, and wash and spin cycle times.
2. Fisher, Sanyo, and others make fuzzy logic camcorders, which offer fuzzy focusing and image stabilization.
3. Mitsubishi manufactures an air conditioner that employs fuzzy systems to control temperature changes according to human comfort indices.

The number of fuzzy consumer products and fuzzy applications involving new patents is increasing so rapidly that it is not possible to offer a limited list of applications. It is this wealth of deployed, successful applications of fuzzy technology that is responsible for the current interest in fuzzy systems.

1.6. BEYOND FUZZY SYSTEMS: SOFT COMPUTING AND COMPUTATIONAL INTELLIGENCE

Viewed from a broad perspective, fuzzy logic is a constituent of an emerging research area, called soft computing, a term coined by Zadeh [2]. It is believed that the most important factor that underlies the marked increase in machine intelligence nowadays is the use of soft computing to imitate the human mind's ability to effectively employ approximate rather than exact modes of reasoning.

Unlike traditional hard computing whose prime goals are precision, certainty, and rigor, soft computing tolerates imprecision, uncertainty, and partial truths. The primary objective of soft computing is to take advantage of such tolerance to achieve tractability, robustness, a high level of machine intelligence, and lower costs. In addition to fuzzy logic, other principal constituents of soft computing are neural networks, probabilistic reasoning, which includes genetic algorithms, evolutionary programming, belief networks, chaotic systems, and parts of learning theory.

Among these, genetic algorithms and evolutionary programming are similar to neural networks in that they are based on low-level microscopic biological models.

They evolve toward finding better solutions to problems, just as species evolve toward better adaptation to their environments. It is also worth noting that fuzzy logic, neural networks, genetic algorithms, and evolutionary programming are also considered the building blocks of computational intelligence as conceived by James Bezdek [3]. Computational intelligence is low-level cognition in the style of the human mind and is in contrast to conventional (symbolic) artificial intelligence. In the partnership of fuzzy logic, neural networks, and probabilistic reasoning, fuzzy logic is concerned mainly with imprecision and approximate reasoning, neural networks with learning, and probabilistic reasoning with uncertainty. Since fuzzy logic, neural networks, and probabilistic reasoning are complementary rather than competitive, it is frequently advantageous to employ them in combination rather than exclusively. A number of excellent texts exist on fuzzy system theory [4–9].

1.7. FUZZY THEORY IN ELECTRIC POWER SYSTEMS

With the remarkable and successful penetration of fuzzy systems into manufacturing, appliances, and computer products, their applications in power systems are beginning to mature and receive wider acceptance in the electric power community. The application of fuzzy set theory to power systems is a relatively new area of research.

Concepts of fuzzy set theory were first introduced in solving power system long-range decision-making problems in the late 1970s. However, substantial interest in its applications to power areas is fairly recent. While conventional analytical solution methods exist for many problems in power system operation, planning, and control, their formulation of real-world problems suffers from restrictive assumptions. Even with these assumptions, solving large-scale power system problems is not trivial. Moreover, many uncertainties exist in a significant number of problems because power systems are large, complex, widely spread geographically, and influenced by unexpected events. These factors make it difficult to deal effectively with many power system problems through strictly conventional approaches alone. Therefore, areas of computational (artificial) intelligence emerged in recent years in power systems to complement conventional mathematical approaches and proved to be effective when properly coupled together.

In conceptualizing power system problems, the expert's empirical knowledge is generally expressed by language containing ambiguous or fuzzy descriptions. As a result, classical Boolean logic may not be a valid tool to represent such expertise. Fuzzy logic, on the other hand, is a natural choice for this purpose.

The growing number of publications on applications of fuzzy-set-based approaches to power systems indicates its potential role in solving power system problems. Results obtained so far are promising, but fuzzy set theory is not widely accepted. The reasons for its lack of acceptance include the following:

- Misunderstanding of the concept
- Excessive claims of some researchers
- Lack of implemented and available systems
- Its status as a new theory

Expert systems and other areas of artificial intelligence were introduced to solve power system operation planning and control problems. Expert systems are typically based on utilizing domain expert's knowledge. Some problems, such as diagnosis (especially transformer/generator malfunction diagnosis), alarm processing, and others, can be solved independently by expert system approaches. It is frequently difficult to make expert systems work efficiently because crisp representation of human empirical knowledge (usually expressed in natural languages and contain inherently uncertain representations) is very difficult and lacks flexibility.

Unexpected events and their uncertainties are traditionally represented by probability. However, it has recently been made clear that some of the uncertain factors are intrinsically of a fuzzy nature and are difficult to manage properly using probabilistic approaches.

There are problems in power systems that contain conflicting objectives. In power system operation, economy and security, maximum load supply, and minimum generating cost are conflicting objectives. The combination of these objectives by weighting coefficients is the traditional approach to such problems. Fuzzy set theory offers a better compromise and obtains solutions that cannot be easily found by weighting methods. The benefits of fuzzy set theory over traditional methods are as follows:

- Provides alternatives for the many attributes of objectives selected
- Resolves conflicting objectives by designing weights appropriate to a selected objective
- Provides the capability for handling ambiguity expressed in diagnostic processes, which involves symptoms and causes

Power system components have physical and operational limits that are usually described as hard inequality constraints in mathematical formulations. Enforcing minor violations of some constraints (practically acceptable) increases the computational burden and decreases the efficiency and may even prevent finding a feasible solution. In practice, certain slight violations of the inequality constraints are permissible. This means that there is not a clear constraint boundary and the constraints can be made soft. Traditionally, this problem has been managed by modifying either the objective function or the underlying iterative process. The fuzzy set approach inherently incorporates soft constraints and thus simplifies implementation of such considerations.

In the area of power system control, optimal control theory is often applied to design controllers to enhance system stability. Since power systems are large and nonlinear, simplifying assumptions are necessary in the design of such controllers. Due to model dependence, the controller's adaptability and robustness are problematic. Recently developed fuzzy-logic-based controllers show promise for robust performance and adaptive schemes.

With advances in fuzzy set theory and achievements made in applications to other areas, there is a need to provide a summary of advances in the applications of fuzzy theory to power system problems.

Momoh, Ma, and Tomsovic [10], suggest applying the following steps when fuzzy set theory is used to solve power system problems:

- *Description of original problem*: The problem to be solved should first be stated mathematically and linguistically.
- *Defining thresholds for variables*: For a given variable, there is a specific value with the greatest degree of satisfaction evaluated from empirical knowledge, and a certain deviation is acceptable with decreasing degree of satisfaction until there is a value that is completely unacceptable. The two values corresponding to the greatest and least degree of satisfaction are termed thresholds.
- *Fuzzy quantization*: Based on the threshold values already determined, proper forms of membership functions are constructed. The functions should reflect the change in degree of satisfaction with the change in variables evaluated by experts.
- *Selection of the fuzzy operations*: In terms of the practical decision-making process by human experts, a proper fuzzy operation is selected so that the results obtained are like those obtained by experts. The interpretation of results using fuzzy systems is based on domain experts' reasoning. Therefore, at this level a hybrid fuzzy set–expert system scheme is desirable. It helps to remove any ambiguity that may occur in problem solving.

1.8. SOME AREAS OF FUZZY APPLICATIONS IN POWER SYSTEMS

Fuzzy applications in electric power systems can be classified as dealing with the following:

- *Planning*: includes system expansion planning and long-midterm scheduling.
- *Operations*: includes security assessment, forecasting, controllers, and diagnosis.

1.8.1. Expansion Planning

There are a number of judgments based on experience and expert opinion that are crucial in decision making for power system expansion planning. Usually it is awkward to capture experience within the constraint formulations of conventional optimization models. This is because many factors, such as load demand levels, new stations locations, environmental effects, and so on, have a decisive effect on the decision making and yet are difficult to represent deterministically. Further, the objectives and constraints are uncertain or competing. In fact, the decision-making process in power system expansion planning is to a large extent qualitative and can be described more flexibly and intuitively by fuzzy set concepts.

1.8.2. Long- and Midterm Scheduling

Power system long- and midterm scheduling problems, such as annual maintenance scheduling, seasonal fuel scheduling, and midterm operation mode studies, are solved by various optimal and heuristic methods. The problems are characterized by many complications and uncertainties. Accurate formulations are often difficult and conventional optimization methods are not efficient. Moreover, it is more reasonable to represent constraints as soft (the fuzzy degree of satisfaction expression permits an engineering acceptable violation of constraints) than as hard. The combination of conventional methods with fuzzy sets may constitute an effective approach to solve these problems.

Fuzzy systems can play an important role in power system operation and planning optimization. Several publications have used fuzzy sets to manage conflicting objectives and soft constraints. This scheme not only makes the problem formulation more flexible, but if applied correctly, it can also improve the computational efficiency.

1.8.3. Dynamic Security Assessment

Dynamic security assessment (DSA) is a major application in power system operation and many techniques have been proposed for its solution. Since system security level varies according to engineering-economic considerations, the reliability of protective relays, the quality of the models used, and the risk of various faults, it may not be reasonable to say that the system is definitely secure or not using conventional binary logic. Present practice in DSA is to conduct off-line studies for a wide range of likely system conditions and network configurations. In on-line applications the results of off-line studies are not directly available but operators are allowed to rely on their own judgment and knowledge acquired in off-line studies and experience gathered over a long period of time. Fuzzy set theory may be useful in building an expert system for DSA based on the operator's empirical knowledge.

1.8.4. Load Forecasting

Power system load is influenced by many factors, such as weather, economic and social activities, and different load components (residential, industrial commercial, etc.). By analysis of only historical load data, it is difficult to obtain accurate load forecasts. The relation between load and independent variables is complex, and it is not always possible to fit the load curve using statistical models. Expert system approaches have shown advantages over conventional methods. The numerical aspects and uncertainties of this problem appear suitable for fuzzy methodologies.

1.8.5. Fuzzy Logic Controllers

Based on the number of publications on the subject, power system control problems are the most popular areas for fuzzy-set-based approaches. In fact, many achievements in the field of fuzzy control have been seen in other industries.

Fuzzy logic controllers are mainly used for power system excitation and converter controls. In traditional controller design, a system model needs to be constructed and control laws are derived based on analysis of the model. Because of nonlinearity, it is nearly always necessary to linearize the system model, and then the linear controllers are used to control the nonlinear system. One advantage of fuzzy logic over other forms of knowledge-based controllers lies in the interpolative nature of fuzzy control rules. The overlapping fuzzy antecedents to the control rules provide transitions between the control actions of different rules. Because of this interpolative quality, fuzzy logic controllers usually require far fewer rules than other knowledge-based controllers. Fuzzy logic controllers have received much attention in recent years, since they are more model independent, show high robustness, and can adapt.

1.8.6. Diagnosis

Human experts play central roles in troubleshooting or fault analysis. In power systems, it is required to diagnose equipment malfunctions as well as disturbances. The information available to perform equipment malfunction diagnosis is most of the time incomplete. In addition, the conditions that induce faults may change with time. Subjective conjectures based on experience are necessary. Accordingly, the expert systems approach has proved to be useful. As stated previously, fuzzy theory can lend itself to the representation of knowledge and the building of an expert system.

1.9. OUTLINE OF THE BOOK

Our discussion begins with Chapter 2 where we offer a summary of fundamentals of fuzzy systems. In Chapter 3, it is pointed out that utilities invest a good deal of time and resources in equipment monitoring and maintenance to anticipate failures or accelerated aging in power equipment. Such monitoring includes regular insulation condition tests for switching devices, reactors, power transformers, generator windings, and so on. In general, many of the indicators of equipment condition are imprecise and/or unreliable. Engineers must have considerable experience with a particular test before that test becomes useful. Several utilities have developed expert systems to codify this experience and improve knowledge of the breakdown process. The authors begin by a review of elements of fuzzy logic as a prelude to discussing possibility theory. This is followed by an example representing a simplified version of a transformer diagnostic and monitoring system. A proposed implementation for processing diagnostic information is given and evaluated. The chapter emphasizes uncertainty modeling of diagnostic problems. Fuzzy information methods are employed to represent quantitatively the diagnostic capability of a system. Further, several methods are discussed for extracting information from test data and evaluating system performance.

In Chapter 4, El-Sharkawi, Marks II, Streifel, and Kerszenbaum discuss detection and localization of shorted turns in the DC field winding of turbine-generator rotors using novelty detection and fuzzified neural networks. Use of neural networks with fuzzy logic outputs and traveling-wave techniques is shown to be an accurate locator of shorted turns in turbo-generator rotors. The technique also applies to transformers and other devices containing symmetrical windings. The technique is extended to operational rotors by the use of a novelty filter. The forms of shorted-turn detection show great promise in the monitoring of high-speed turbo-generators. Since introduction of shorts into on-line rotors is not possible, the explicit verification of any fault detection technique is not possible without the availability of a machine with a suspected shorted turn. Signature signals could be collected before the suspect rotor is dismantled for maintenance. After the rotor is repaired and brought back on line, healthy signature signals can be collected. The healthy regions and thresholds can then be established using the proposed techniques. The signature signals recorded before correction of the fault can then be processed by the detection algorithm.

Low-frequency oscillations are a common problem in large power systems. A power system stabilizer (PSS) can provide supplementary control signals to the excitation system and/or the speed governor system of the electric-generating unit to damp these oscillations and to improve its dynamic performance. Chapters 5 and 6 are devoted to this important topic. In Chapter 5, Malik and El-Metwally describe the structure and design of a fuzzy logic controller, and an algorithm to tune its parameters to achieve the desired performance is described. Two rule generation methods to automatically generate the fuzzy rule set are proposed. The application of the fuzzy logic controller as a power system stabilizer is investigated by simulation studies on a single-machine infinite-bus system and on a multimachine power system. Implementation of the fuzzy-logic-based power system stabilizer on a microcontroller and results of experimental studies on a physical model of a power system illustrate the effectiveness of the fuzzy-logic-based controller. Results of simulation and experimental studies look promising.

Continuing with power system stabilization, in Chapter 6, Hiyama presents a study on fuzzy logic power system stabilizers using polar information. Here, advanced fuzzy logic control rules are introduced based on three-dimensional information of generator acceleration, speed, and phase angle. Stabilizing signals are revised at every sampling instant and fed back to the excitation control loop of the generator. Simulation and laboratory studies are reported to demonstrate the technique's effectiveness. The results have been implemented on a prototype tested on hydro units in the Japanese KEPCO system.

The second contribution of Hiyama is on fuzzy logic switching control for FACTS devices, presented as Chapter 7. Here a fuzzy logic switching control scheme is proposed for devices such as the thyristor-controlled series capacitor modules, static var compensators (SVCs), and braking resistors (BRs). The stable region of operation is highly enlarged by the fuzzy logic switching of flexible AC transmission system (FACTS) devices. The coordination with power system stabilizers is shown to be effective to enlarge the stable region. The coordination between the BR and the SVC is also effective when the rating of the BR is small. Through the simulations, the robustness of the proposed control scheme is verified.

In Chapter 8 the effects of uncertain load in real-time and off-line power network modeling are discussed. Lu and Leou describe different approaches for representing uncertain load in power systems. In practice, load data can only be known within some finite precision. This being more the case as the study represents conditions that are more distant into the future. In order to avoid a large amount of repeated calculations and to take into account load uncertainties, it seems beneficial to represent the uncertain load using two approaches discussed in this chapter.

In building network models for power system analysis, if knowledge of network parameters is not complete but operation involves repetition of events with fixed laws governing it, one could represent the information by probability distributions. However, if the knowledge available is not sufficient to build the density function of the distribution but one still has qualitative information on the data to be represented, a possibility representation or use of fuzzy numbers could be useful. Probability theory and possibility theory are two complementary views of uncertainty. Uncertainties in loads or generations that do not have definite probability distribution can be incorporated in power system models by using the possibility approach to give a better representation of system behavior. As a consequence of dealing with fuzzy events, a whole set of load scenarios is analyzed at one time, avoiding the need for expensive simulation studies.

Miranda treats power system reliability in Chapter 9. Here the author concentrates mainly on reliability assessment for mid- to long-term purposes. Three types of models are discussed. In type I, only a fuzzy description of the system load is available. For type II fuzzy reliability assessment, component reliability indices are fuzzy. Extending the concept, we can also deal with a type III model.

In Chapter 10, Matsumoto discusses an operation support expert system for startup schedule optimization in fossil power plants. The chapter describes expectations of fuzzy theory in fossil power plant operation and two types of expert systems applied to operation support systems for a conventional one-through-type supercritical pressure fossil power plant and a gas and steam turbine combined-cycle power plant. Fuzzy models of expertise are introduced to modify the plant startup schedule. The most remarkable feature of this approach is that the quantitative optimum schedule is obtained through iterative modification of the schedule from a combination of qualitative knowledge and plant dynamic simulations. Simulation results with these two operation support expert systems demonstrate that plants are started quickly and accurately through the optimum startup schedule. Operator work is reduced in monitoring and executing startup schedules with functions for on-line assessment and off-line learning of plant dynamics. Convergence of the schedule optimization is fast compared with conventional operations research techniques. The expert systems are expected to contribute to reducing operators' work burden and to harmonize machine operation not only for economical aspects but also for environmental advantages.

In Chapter 11, Shahidehpour and Ferrero present a methodology to evaluate power purchases in an uncertain environment. Power generation, line flows, and prices are considered as triangular fuzzy numbers. Local generation and power purchases are control variables in the optimization procedure. The proposed methodology computes the range of control variables that satisfy the set of constraints as well as a certain reduction in the operation cost. The range of control variables is correlated with the desired cost reduction (goal). The lower the desired cost reduction, the narrower the range of control variables that satisfy the set of constraints. The utility decision maker reduces the goal iteratively until no feasible solution is found, obtaining the lowest operation cost while satisfying the operational constraints. The degree of acceptance of variables in the problem can be measured with the left and right spreads of the fuzzy numbers. When more uncertain variables are introduced in the problem, the degree of uncertainty of the obtained solution grows. The authors point out that the proposed method can be extended to include extra constraints related with operational practices in utilities.

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