# Chapter IV
# Fuzzy Systems Applications to Power Systems

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**Abstract**: This chapter overviews the applications of fuzzy logic in power systems. Emphasis is placed on understanding the types of uncertainties in power system problems that are well-represented by fuzzy methods. Specific examples in the areas of diagnostics and controls are used to illustrate such concepts.

**Keywords**: Distribution systems, fuzzy control, fuzzy numbers, fuzzy linear programming, preventive maintenance, reliability.

## 1 Introduction

The purpose of this chapter of the short-course is to overview the relevance of fuzzy techniques to power system problems, to provide some specific example applications and to provide a brief survey of fuzzy set applications in power systems. Fuzzy mathematics is a broad field touching on nearly all traditional mathematical areas, the ideas presented in this discussion are intended to be representative of the more straightforward application of these techniques in power systems to date. Fuzzy logic technology has achieved impressive success in diverse engineering applications ranging from mass market consumer products to sophisticated decision and control problems [1, 2]. Applications within power systems are extensive with more than 100 archival publications in a 1995 survey [3]. Several of these applications have found their way into practice and fuzzy logic methods have become an important approach for practicing engineers to consider. Here, the focus is on the more general concepts. The reader is referred to [3,4] for a more detailed survey of the literature.

Fuzzy sets were first proposed in the early 1960s by Zadeh [5] as a general model of uncertainty encountered in engineering systems. His approach emphasized modeling uncertainties that arise commonly in human thought processes. Bellman and Zadeh write: “Much of the decision-making in the real world takes place in an environment in which the goals, the constraints and the consequences of possible actions are not known precisely” [6]. Fuzzy sets began as a generalization of conventional set theory. Partially as result of this fact, fuzzy logic remained the purview of highly specialized technical journals for many years. This changed with the highly visible success of numerous control applications in the late 1980s. Although fuzzy mathematics arose and developed from the systems area, it perhaps belongs best to in the realm of Artificial Intelligence (AI) techniques as an interesting form of knowledge representation. Still, the primary development of fuzzy techniques has been outside the mainstream AI community.

Uncertainty in fuzzy logic typically arises in the form of vagueness and/or conflicts, which are not represented naturally within the probabilistic framework. To be sure, uncertainty in reasoning may arise in a variety of ways. Consider the most common sort of discourse about a system among experts, and say to be more specific, a statement relevant to contaminants in the insulating oil of high voltage transformers

*The moisture level in the oil is high*

While this is a vague statement that does not indicate an exact measurement of the moisture, it does convey information. In fact, one might argue that this conveys more information than merely the actual moisture measurement since the qualifier “high” provides an assessment of the oil condition. Clearly, such a statement contains uncertainty, that is, the moisture level, the severity of the high reading, the implication of such moisture content, and so on, are all imprecise and may require clarification. Fuzzy sets emphasize the importance of modeling such uncertainty.

With some effort, traditional probabilistic methods can be adapted to these problems. Still, researchers in the fuzzy set area have found that this is not usually an effective approach. To begin, the fuzzy set approach poses new views of systems that has resulted in such novel applications as fuzzy logic control. More importantly, fuzzy sets create a framework for modeling that does not exist under probability. Less formal methods, such as, certainty factors do not allow for as systematic as an approach. Still, there remains controversy among researchers about the need for fuzzy mathematics and a variety of techniques have arisen in both the Systems and Control community and the AI community to address similar problems. This paper will sidestep such controversy but it is worth noting the large number of successful applications of fuzzy logic and while subsequent developments may lead to different techniques, fuzzy logic has already played an important role in bringing this class of problems to light.

To begin with some generalities, some of the most useful capabilities and features provided by modeling in fuzzy set approaches are:

- Representation methods for natural language statements,
- Models of uncertainty where statistics are unavailable or imprecise, as in say, intervals of probability,
- Information models of subjective statements (e.g., the fuzzy measures of belief and possibility) ,
- Measures of the quality of subjective statements (e.g., the fuzzy information measures of vagueness and confusion) ,
- Integration between logical and numerical methods,
- Models for soft constraints,
- Models for resolving multiple conflicting objectives,
- Strong mathematical foundation for manipulation of the above representations.

Uncertainty arises in many ways within power system problems. Historically, uncertainty has been modeled based on randomness, as in, stochastic models for random load variations, noise in measurements for state estimation, fluctuations in model parameters, and so on. In practice, uncertainty certainly arises from the knowledge of the system performance and goals of operation as well. Clearly, the objectives in most decision problems are subjective. For example, the relative importance of cost versus reliability is not precise. The underlying models of the system also exhibit uncertainty through approximations arising from, linearized models and other modeling approximations, parameter variations, costs and pricing, and so on.

Heuristics, intuition, experience, and linguistic descriptions are obviously important to power engineers. Virtually any practical engineering problem requires some “imprecision” in the problem formulation and subsequent analysis. For example, distribution system planners rely on spatial load forecasting simulation programs to provide information for a various planning scenarios [7]. Linguistic descriptions of growth patterns, such as, fast development, and design objectives, such as, reduce losses, are imprecise in nature. The conventional engineering formulations do not capture such linguistic and heuristic knowledge in an effective manner.

Subjective assessments of the above uncertainties are needed to reach a decision. These uncertainties can be broadly separated into two groups: 1) measurements and models of the system and 2) constraints and objectives arising from the decision-making process. Examples of uncertainties arising in power systems based on such a classification are shown in Tables 1 and 2.

Table 1. Examples of Measurements/Models with Fuzziness.

| |
|---|
| Contingencies |
| Equipment failure modes |
| Linear approximations |
| Measurement noise |
| Metering errors |
| Modeling errors |
| Occurrence times of events |
| Reduced-model parameters |
| Predicted demand |
| System dynamics |

Table 2. Examples of Constraints/Objectives with Fuzziness.

| |
|---|
| Acceptable security risk |
| Assessment of customer satisfaction |
| Economic objectives |
| Environmental objectives |
| Equipment loading limits |
| Normal operational limits |
| Power quality objectives |
| Security objectives |
| Stability limits |

This rest of this chapter begins with an overview of applications within power systems. This is followed by a general section on fuzzy logic techniques and methods. Subsequently, examples of a system for stabilization control is presented.

## 2 Power System Applications

Fuzzy sets have been applied to many areas of power systems. Table 3 is a list of the more common application areas. This section discusses the applications based on the particular fuzzy method used. There are essentially three groups of applications: rule-based systems with fuzzy logic, fuzzy logic controllers and fuzzy decision systems.

### 2.1 Rule-based Fuzzy Systems

The most common application of fuzzy set techniques lies within the realm of rule-based systems. Here, uncertainties are associated with each rule in the rule-base. For example, consider a transformer diagnostics problem where dissolved gas concentrations indicate incipient faults. A sample statement as earlier for transformer diagnostics might be:

Table 3. Fuzzy Set Application Areas in Power Systems.

| |
|---|
| Contingency analysis |
| Diagnosis/monitoring |
| Distribution planning |
| Load frequency control |
| Generator maintenance scheduling |
| Generation dispatch |
| Load flow computations |
| Load forecasting |
| Load management |
| Reactive power/voltage control |
| Security assessment |
| Stabilization control (PSS) |
| Unit commitment |

*A high level of hydrogen in the insulating oil of a transformer often indicates arcing*

The two uncertainties to be modeled are "often" and "high," which are most easily represented as a fuzzy measure and fuzzy set, respectively. Strict mathematical methods have been developed for manipulating the numerical values associated with such uncertainty. Note equipment diagnostics tend to be a particularly attractive area for application since developing precise numerical models for failure modes is usually not practical.

It is difficult to know just how many rule-based systems in power systems employ fuzzy logic techniques as many development tools have built in mechanisms for managing uncertainty and developers themselves may be unaware that they are using fuzzy logic. For example, the widely used certainty factors method is a special case of a fuzzy measurement.

2.2 Fuzzy Controllers

The traditional control design paradigm is to form a system model and develop control laws from analysis of this model. The controller may be modified based on results of testing and experience. Due to difficulties of analysis, many such controllers are linear. The fuzzy controller approach is to somewhat reversed. General control rules that are relevant to a particular system based on experience are introduced and analysis or modeling considerations come later. For example, consider the following general control law for a positioning system

*IF error is small and positive*
*AND error change is large and negative*
*THEN control output is small and negative*

This rule implements a control concept for anticipating the desired position and reducing the control level before the set point is reached in order to avoid overshoot. The quantities "small" and "large" are fuzzy quantities. A full control design requires developing a set of control rules based on available inputs and designing a method of combining all rule conclusions. The precise fuzzy membership functions depend on the valid range of inputs and the general response characteristics of the system. Within power systems, fuzzy logic controllers have been proposed primarily for stabilization control.

2.3 Fuzzy Decision-Making and Optimization

The broadest class of problems within power system planning and operation is decision-making and optimization, which includes transmission planning, security analysis, optimal power flow, state estimation, and unit commitment, among others. These general areas have received great attention in the research community with some notable successes; however, most utilities still rely more heavily on experts than on sophisticated optimization algorithms. The problem arises from attempting to fit practical problems into rigid models of the system that can be optimized. This results in reduction in information either in the form of simplified constraints or objectives. The simplifications of the system model and subjectivity of the objectives may often be represented as uncertainties in the fuzzy model.

Consider optimal power flow. Objectives could be cost minimization, minimal control adjustments, minimal emission of pollutants or maximization of adequate security margins. Physical constraints must include generator and load bus voltage levels, line flow limits and reserve margins. In practice, none of these constraints or objectives are well-defined. Still, a compromise is needed among these various considerations in order to achieve an acceptable solution. Fuzzy mathematics provides a mathematical framework for these considerations. The applications in this category are an attempt to model such compromises.

## 3 Basics of Fuzzy Mathematics

In this section, some basics of fuzzy mathematics are introduced. Fuzzy logic implements experience and preferences through membership functions. The membership functions have different shapes depending on the designer's preference and experience. Fuzzy rules may be formed that describe relationships linguistically as antecedent-consequent pairs of IF-THEN statements. Basically, there are four approaches to the derivation of fuzzy rules: (1) from expert experience and knowledge, (2) from the behavior of human operators, (3) from the fuzzy model of a process, and (4) from learning. Linguistic variables allow a system to be more understandable to a non-expert operator. In this way, fuzzy logic can be used as a general methodology to incorporate knowledge, heuristics or theory into controllers and decision-making.

Many of the fundamental techniques of fuzzy sets are widely available so only a fairly brief review is given in the following. The lesser-known methodology of fuzzy measures and information theory is developed more fully here. More extensive treatment of the mathematics can be found in [8,9].

A fuzzy set is a set of ordered pairs with each containing an element and the degree of membership for that element. A higher membership value indicates that an element more closely matches the characteristic feature of the set. For fuzzy set *A*:

$$A = \{(x, \mu_A(x)) \mid x \in \mathrm{X}\} \tag{1}$$

where $\mathrm{X}$ is the universe, $\mu_A(x)$ represents the membership function and for normalized sets $\mu : \mathrm{X} \to [0,1]$. For example, one could define a membership function for the set of numbers much greater than 10 as follows:

$$\mu_{>>10}(x) = \frac{x^2}{100 + x^2}$$

Most commonly, the logical operations (intersection, union and complement) on sets are defined as:

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \tag{2}$$

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{3}$$

$$\mu_{\overline{A}}(x) = 1 - \mu_A(x) \tag{4}$$

Note that if set containment is defined as $A \subseteq B$ if $\forall \mathrm{x} \in \mathrm{X}$ $\mu_A(x) \le \mu_B(x)$, then the following always holds $A \subseteq A \cup B$ and $A \cap B \subseteq A$. Other operators from within the triangular norm and co-norm classes may be more appropriate than the above functions [10]. For example, the framework of Dombi [11], been used extensively by the author.

$$\mu_{A \cap B}(x) = \frac{1}{1 + ((\frac{1}{\mu_A(x)} - 1)^{\lambda} + (\frac{1}{\mu_B(x)} - 1)^{\lambda})^{\frac{1}{\lambda}}} \tag{5}$$

with $\lambda \ge 1$. Increasing the parameter $\lambda$ will increase the emphasis on the smaller membership value so that, for example, one could emphasize a line of reasoning that considered less likely possibilities. Also, one can define the union operation by allowing $\lambda \le -1$. It is often necessary to generate a crisp (non-fuzzy) set from a fuzzy set, and one can define an $\alpha$-cut as:

$$A_\alpha = \{x \mid \mu_A(x) \ge \alpha\} \tag{6}$$

with $A_\alpha$ a crisp set containing all elements of the fuzzy set *A* which have at least a membership degree of $\alpha$.

In assessing system states, uncertainty arises either from the measurement or from incomplete knowledge of the system. Traditionally, this type of uncertainty is modeled as random noise and so managed with probability methods. Fuzzy measures are a generalization of probability measures such that the additivity restriction is removed. Specifically, a fuzzy measure *G* is defined over the power set of the universe $\mathrm{X}$ (designated as $\mathsf{P}(\mathrm{X})$):

$$G : \mathsf{P}(\mathrm{X}) \to [0,1]$$

with:

- $G(\phi) = 0$ and $G(\mathrm{X}) = 1$ (Boundary conditions)
- $\forall A, B \in \mathsf{P}(\mathrm{X})$ if $A \subseteq B$ then $G(A) \le G(B)$. (Monotonicity)
- For any sequence $A_1 \subseteq A_2 \subseteq \ldots \subseteq A_n$ then $\lim_{i \to \infty} G(A_i) = G(\lim_{i \to \infty} A_i)$. (Continuity)

where $\phi$ is the empty set. There are three particularly interesting cases with this definition of a fuzzy measure: probability, belief (a lower bound of the probability) and plausibility (an upper bound of the probability). If the following additivity condition is satisfied then *G* is a probability measure, represented by *P*:

$$P(\bigcup_{i=1}^{n} A_i) = \sum_{i=1}^{n} P(A_i) - \sum_{i=1}^{n} \sum_{j=i+1}^{n} P(A_i \cap A_j) + \ldots + (-1)^n P(A_1 \cap A_2 \cap \ldots \cap A_n) \tag{7}$$

If this equality is replaced by (8) below, then *G* is called a belief measure and represented by *Bel*:

$$Bel(\bigcup_{i=1}^{n} A_i) \ge \sum_{i=1}^{n} Bel(A_i) - \sum_{i=1}^{n} \sum_{j=i+1}^{n} Bel(A_i \cap A_j) + \ldots + (-1)^n Bel(A_1 \cap A_2 \cap \ldots \cap A_n) \tag{8}$$

and finally a plausibility measure results if the following holds instead of (7) or (8):

$$Pl(\bigcap_{i=1}^{n} A_i) \leq \sum_{i=1}^{n} Pl(A_i) - \sum_{i=1}^{n} \sum_{j=i+1}^{n} Pl(A_i \cup A_j) + ... + (-1)^n Pl(A_1 \cup A_2 \cup ... \cup A_n) \quad (9)$$

and finally it is useful to summarize these expressions in the following way, $\forall A \in X$:

- $Bel(A) + Bel(\overline{A}) \leq 1$
- $Pl(A) + Pl(\overline{A}) \geq 1$
- $P(A) + P(\overline{A}) = 1$
- $Pl(A) \geq P(A) \geq Bel(A)$

These expressions and consideration of the forms in (8-9) lead to the interpretation of belief representing supportive evidence and plausibility representing non-supportive evidence. This is best illustrated by considering the state descriptions for each of the measures when nothing is known about the system (the state of *total ignorance*). A plausibility measure would be one for all non-empty sets; and belief would be zero for all sets excepting the universe $X$. Conversely, it would be typical in probability to assume a uniform distribution so that all states were equally likely. Thus, an important difference in the use of fuzzy measures is in terms of representing what is unknown.

The use of the above structure in a problem could be to focus on incrementally finding a solution to a problem by initially assuming all equipment states are possible (plausibility measure of one) but no specific state can be assumed (belief measure of zero). That is, one begins from the state of ignorance. As evidence is gathered during diagnosis, supportive evidence will increase the belief values of certain events and non-supportive evidence will decrease the plausibility of other events. This description provides a natural way of representing tests which are geared either towards supporting or refuting specific hypotheses.

The fuzzy sets and measures framework defined above provides the fundamentals for representing uncertainty. To reach decisions and use the representative powers of fuzzy sets requires further manipulative techniques to extract information and apply knowledge to the data. A generalized framework called a body of evidence is defined to provide a common representation for information. Evidence will be gathered and represented in terms of fuzzy relations (sets) and fuzzy measures and then translated to the body of evidence framework. Techniques will be employed to extract the most reliable information from the evidence. Let the body of evidence be represented as:

$$m : \mathcal{P}(X) \rightarrow [0,1]$$

with:

- $m(\phi) = 0$ (Boundary condition)
- $\sum_{A \in \mathcal{P}(X)} m(A) = 1$. (Additivity)

It is important to emphasize that $m(A)$ is not a measure but rather can be used to generate a measure or conversely, to be generated from a measure. A specific basic assignment over $\mathcal{P}(X)$ is often referred to as a body of evidence. Based on the above axioms, it can be shown [14] that:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (10)$$

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B) \quad (11)$$

and conversely that:

$$m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(A) \quad (12)$$

where $|\cdot|$ is set cardinality. These equations show us another view of belief and plausibility. Belief measures the evidence that can completely (from the set containment) explain a hypothesis. Plausibility measures the evidence that can at least partially (from the non-empty intersection) explain a hypothesis. In many cases, one wants to combine information from independent sources. Evidence can be "weighted" by the degree of certainty among bodies of evidence. Such an approach leads to the Dempster rule of combination where given two independent bodies of evidence $m_1$ and $m_2$ and a set $A \neq \phi$:

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A} m_1(B) \cdot m_2(C)}{1 - K} \quad (13)$$

where:

$$K = \sum_{B \cap C = \phi} m_1(B) \cdot m_2(C) \quad (14)$$

The factor $K$ ensures that the resulting body of evidence is normalized in case there exists evidence, which is irreconcilable (evidence on mutually exclusive sets). The above framework of measures appears best suited diagnostic problems and associated reasoning.

## 4 Example Control Application

Fuzzy logic control (FLC) has generally been applied to difficult to model systems that do not require precise control. This sections presents an application for power system control following disturbances where the emphasis is on stabilization during and immediately following a fault.

The large interconnected power system must maintain voltage and synchronous frequency within a very narrow range. In addition, loading constraints on individual system components must be observed. The system constantly undergoes disturbances from minor fluctuations in load, generation and so on, which result in small easily damped oscillations if the system is not loaded too heavily. Occasionally, the system experiences more severe disturbances from line faults or other equipment outages. During these disturbances, and particularly when the system is heavily loaded, generator controls must act quickly to maintain synchronism and dampen oscillations. Power system stabilizers (PSS) are designed for this purpose.

The PSS increases or decreases generator excitation based on frequency fluctuations. The control problem is difficult as a fault presents a sudden unknown change in the system dynamics and further, the post fault equilibrium point is unknown. Traditionally, this problem has been approached using linear design methods for the PSS and requires extensive simulations of possible faults with subsequent tuning [12]. FLC presents a possibility to address this by designing a controller that focuses on the role of the PSS to provide adequate synchronizing torque rather than the difficult task of developing a precise system model.

The two reasons most often sighted for pursuing fuzzy control are the desire to incorporate linguistic control rules and the need to design a controller without developing a precise system model. It is important to note that the fuzzy logic controller is fully expressive in that it can uniformly approximate any real continuous mapping to arbitrary accuracy. Thus, the power of the fuzzy logic approach stems from the ability to implement linguistic descriptions of control rules for difficult to model systems. One begins from the assumption that the control rules for a system can be expressed adequately by a human expert. The design phase then concerns the refinement of these control rules and the subsequent inference process. Here, it is assumed the control rules are general and given. The controller under consideration here can be classified as a direct adaptive fuzzy controller where only the controller and not the system is modeled by fuzzy logic [13]

While fuzzy logic methods have a well-founded theoretical basis, most of the reported FLC applications require some form of numerical tuning to a specific system to obtain reasonable performance. This numerical tuning generally involves a significant computational effort and may be limited to a narrow range of operation conditions. There is also a need to allow designers to specify desired response characteristics. Note, this allows their expertise to be expressed in two ways: the general control rules of the controller and the desired system response.

### 4.1 A Controller Design Methodology

In general, FLC design consists of the following steps:

1. Identification of input and output variables.
2. Construction of control rules.
3. Establishing the approach for describing system state in terms of fuzzy sets, i.e., establishing fuzzification method and fuzzy membership functions.
4. Selection of the compositional rule of inference.
5. Defuzzification method, i.e., transformation of the fuzzy control statement into specific control actions.

Steps 1 and 2 are application specific and typically straightforward. There are several approaches to Steps 4 and 5 but most of the literature reports using minimum implication and center-of-gravity defuzzification. The design methodology in this tutorial centers on forming general rule membership functions and then determining parameters based on observed response to a disturbance. The controller model is presented first.

Fig. 4. Control Rules

(*Notation: LP = large positive; MP = medium positive; SP = small positive; ZE = zero; SN = small negative; MP = medium negative; LP = large positive*)

| $e$ \ $\dot{e}$ | LN | MN | SN | ZE | SP | MP | LP |
|---|---|---|---|---|---|---|---|
| LN | LP | LP | LP | MP | MP | SP | ZE |
| MN | LP | MP | MP | MP | SP | ZE | SN |
| SN | LP | MP | SP | SP | ZE | SN | MN |
| ZE | MP | MP | SP | ZE | SN | MN | MN |
| SP | MP | SP | ZE | SN | SN | MN | LN |
| MP | SP | ZE | SN | MN | MN | MN | LN |
| LP | ZE | SN | MN | MN | LN | LN | LN |

A block diagram of the feedback controller is shown in Fig. 1. The controller has two inputs: error $e$, and error change, $\dot{e}$, and a single output $u$. For the controller proposed here all three variables must lie in the interval [-1,1]. This is achieved by scaling the physical system variables by appropriate constants and if necessary, limiting the resulting value. A conventional fuzzy logic controller with two inputs is used with rules of the form:

$$R_i\text{: If } e \text{ is } A_i \text{ and } \dot{e} \text{ is } B_i \text{ then } u \text{ is } C_i \qquad (15)$$

where $A_i$, $B_i$ and $C_i$ are convex fuzzy sets. The control output is calculated using the minimum operation for fuzzy implication and center of gravity defuzzification. For $n$ rules:

$$u(e,\dot{e}) = \frac{\sum_{i=1}^{n} \overline{C_i} \cdot \min(\mu_{A_i}(e), \mu_{B_i}(\dot{e}))}{\sum_{i=1}^{n} \min(\mu_{A_i}(e), \mu_{B_i}(\dot{e}))} \qquad (16)$$

$\overline{C_i}$ is defined as the value of $u$ where the fuzzy set $C_i$ obtains a maximum (or median of the interval where the maximum is reached). For the development in this example, the membership functions are triangular form as shown normalized on the interval [-1,1] in Fig. 2. The control rules are shown in Table 4.

The controller inputs of error, $e$, and error change, $\dot{e}$, are scaled by the constants $K_e$ and $K_{\dot{e}}$, respectively, and the control output $u$ by $K$. These constants are analogous to the control gains in a traditional PD controller; however rather than calculating gains, the designer determines a scaling based on the possible magnitude of disturbances. Similar frameworks have been proposed in the literature, e.g. [14]. Here, the $K$ constants are assumed to correspond to the maximum allowable absolute values for the variables within a particular operating regime.

The determination of these $K$ constants is non-trivial and in essence determines the performance of the controller. Improper values for the $K$ constants modifies the control rules and limits the effectiveness of the FLC. For example, a small value for $K_e$ means that control rules in the middle rows of Table 4 will apply less often and the system will be "over" controlled for small errors. There should be guidelines for control engineers to select such parameters independent of the rules or membership functions. In general, numerical tuning may require significant computational effort and the resulting parameter values may not be valid over a wide range of operating conditions.

The problem of concern in this work requires that the

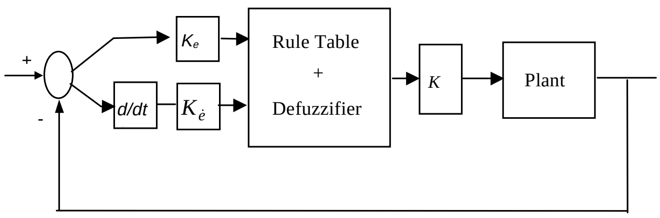


Fig. 1. Block diagram of fuzzy logic controller.

parameters are valid during a disturbance where the system parameters will vary widely so tuning for a particular operating point may not be valid. The proposed approach relies on observation of the response to a nominal proportional gain feedback controller as follows:

1. The fuzzy logic controller is replaced with a controller of constant gain $K$.
2. Response to a set of disturbances, $d_i,\ i \in I$ , are observed for the chosen value of $K$ for a specified interval $T$.
3. The other $K$ constants are then calculated as:

$$K_e = [\max_{i \in I, t \in [0,T]} e_i(t)]^{-1} \qquad (17)$$

$$K_{\dot{e}} = [\max_{i \in I, t \in [0,T]} \dot{e}_i(t)]^{-1} \qquad (18)$$

While this approach assumes a simulator is available, the constants could also be determined from the actual system data.

4.2 Illustrative example

In the following, simulations illustrate the performance of a PSS designed by the above methodology. The fuzzy PSS constants are found by simulations of a step change in mechanical power input using the non-linear model of [15] for a single machine infinite bus system. The PSS used for comparison is designed using a conventional phase lead technique to precisely compensate for the phase lag of the electrical loop. The step response to a three phase fault of duration 0.05 seconds. Results are shown in Fig. 3. The FPSS shows superior to the traditional controller with the parameters chosen exactly by the described methodology. For the more severe disturbances, the FPSS controller has significantly better performance and the design process is significantly simpler.

## 5 Future Trends

Relatively few implemented systems employing fuzzy logic exist in the power industry today. Still, implementation considerations should be primarily the same as those faced with knowledge-based AI techniques, which have been addressed before. So, the discussion here focuses on fundamental questions that need to be more fully understood before fuzzy sets achieve greater impact.

5.1 Membership values

One of the most frequently discussed problems in fuzzy set applications is specification of membership functions. Often a linear form is chosen for computational reasons. In some cases, statistics exist for certain parameters, which can then be adapted to the membership function. More theoretical approaches to this problem also exist [11]. Whatever approach is chosen, it should be kept in mind that the solution should not be highly sensitive to membership values. Philosophically, if a precise membership function is needed to obtain acceptable results than the problem at hand is probably not appropriate for fuzzy techniques or has not been defined properly.

5.2 Fuzzy Operators

With very few exceptions, fuzzy set applications within power systems have relied on minimum and maximum for the intersection and union operators, respectively. Research has shown that these operators do not represent accurately the way most people normally make decisions. It is likely that successful applications will have to adopt other inference operators from the T-norm and T-conorm classes. It has been suggested that operators be developed for specific applications. For example, security and reliability concerns may work best with stricter operators.

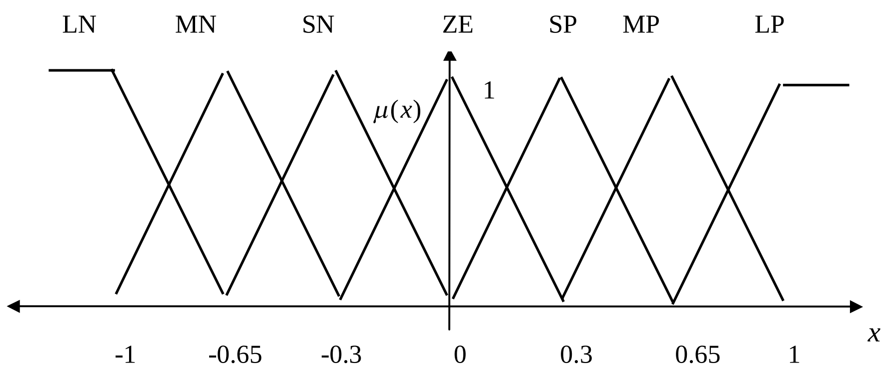


Fig. 2. Normalized membership functions.

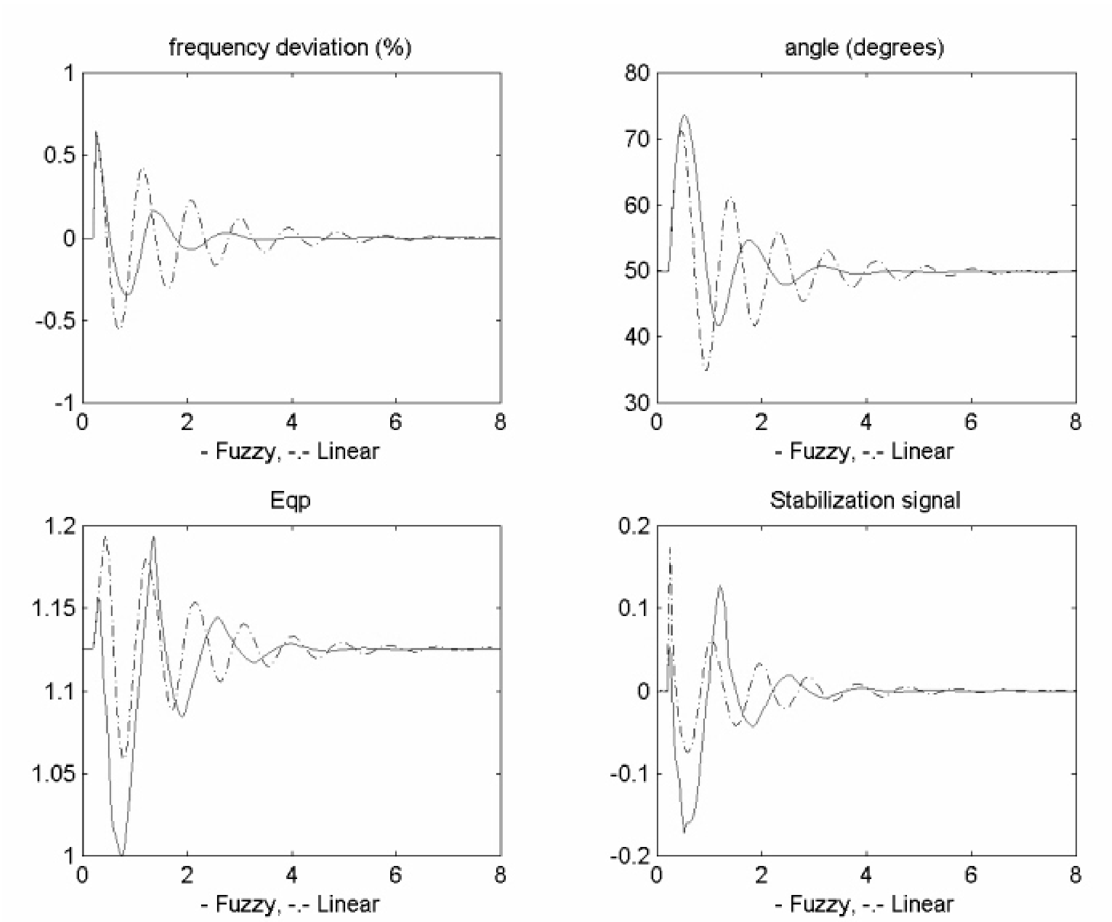


Fig. 3. Simulation results for tuned fuzzy PSS compared to linear PSS.

5.3 Performance analysis

Performance evaluation remains a problem common to many areas of AI applications. This problem is even more of concern with fuzzy sets. The solution is based on subjective and uncertain assessments and so must be subjective and uncertain. In contrast to other AI methods, however, the structure exists within fuzzy mathematics for developing measurements that can indicate the quality of a solution, e.g., the "entropy-like" measures of confusion, dissonance and vagueness. Thus, fuzzy mathematics has the potential to quantify such subjectivity.

5.4 Relation to ANN and other Soft Computational Methods

Both fuzzy sets and Artificial Neural Nets (ANNs) are methods of interpolation. The primary advantage of ANNs over fuzzy sets lies in effective methods for learning from examples; however, knowledge representation is implicit in an ANN, so that, it is difficult to encode a priori knowledge. Conversely, fuzzy set theory provides explicit knowledge representation, yet no specific formulation for learning exists. Several researchers have demonstrated how these approaches complement each other. Techniques from other areas of soft computation, such as, Genetic Algorithms also have shown great potential for supplementing fuzzy methods.

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