A Fuzzy Logic Classifier for Transient Stability Assessment

Almoataz Youssef Abdelaziz

Available at: https://works.bepress.com/almoataz_abdelaziz/4/
ABSTRACT

Transient stability assessment (TSA) of a power system pursues a two-fold objective: first to appraise the system’s capability to withstand major contingencies and second to suggest remedial actions whenever needed. The first objective is the concern of analysis; the second is a matter of control.

To assess transient stability, multitude of techniques are available encompassing traditional time domain state numerical integration, Lyapunov based techniques, probabilistic methods, and recently Artificial Intelligence (AI) techniques.

This paper presents a simple but effective fuzzy logic classifier system for TSA. The fuzzy logic-based rule assessment needs only a fraction of time to solve the classification problem, namely to classify an operating point of the machine as a stable or unstable one. The results revealed that the proposed classifier system is flexible and extendible.

KEYWORDS

Transient Stability, Artificial Intelligence, Fuzzy Logic, Classifier System.

1. INTRODUCTION

Electric power systems are examples of large-scale non-linear systems exhibiting a wide range of stability problems. This is the reason that one of the most important problems in the study of multi-machine power systems is the transient stability assessment. It examines whether on occurrence of a large disturbance, the power system is capable of surviving the ensuing transient and will move into an acceptable steady-state condition.

There are many approaches used to deal with the TSA problem. The traditional numerical integration method [1] discretizes the machine swing equations to obtain the evolution with time of the machine rotor angles. This method is tedious, and not suitable for on-line environment. Lyapunov stability theory of non-linear systems was also used for the TS problem [2]. Even though these methods are accurate, they are computationally tedious. A probabilistic assessment of TS for a multi-machine power system was suggested in [3], in which the random nature of the fault type and location, and of the fault clearing phenomenon were considered in details.

Recently, (AI) has been applied to power system and resulted in an overall improvement of solutions in many areas. The K-means clustering pattern recognition technique was used in out-of-step detection in [4]. Although simple and fast, the performance of classification was good. The authors of [5] have presented a new out-of-step prediction approach based on neural networks with improving the classification performance. Both of the two previous schemes are characterized by simple structure based only on local measurements. The present author presented another AI approach for TSA in [6]. The approach depends on the Inductive Inference Reasoning approach which builds decision rules off-line and they are automatically designed in the form of decision trees built in a top down fashion. The detection of the transient stability condition involves traversing the decision trees for the given operating condition.

The fuzzy sets theory is employed in TSA problem because it can take into account qualitative information about transient stability that remains unutilized by conventional approaches to the problem (human operators stability judging under imprecision). It can also provide the margin of system stability under a given operating condition. The application of fuzzy concepts in TSA was introduced for the first time in [7], where an index providing an evaluation of the system level of security by considering the values of generator accelerations and kinetic energies after the occurrence of a large disturbance was presented. The authors of [8] presented a fuzzy logic classifier for TSA using three variables (load condition, fault location and clearing time) as inputs of the fuzzy classifier. The low correct classification percentage obtained (92 %) was due to the nature of the input variables. A predictive out-of-step relaying approach using fuzzy rule-based classification was presented in [9]. The advantage of this approach is that it does
not need any telemetry equipment since it uses an active power transducer fed from local measurements on the generator terminals to produce the input features to the fuzzy system.

This paper presents another fuzzy logic classifier for transient stability assessment. Compared with recent approaches, the algorithm presented in this paper is very simple, accurate and suitable to be applied for large power systems.

2. FUZZY SETS AND FUZZY SETS OPERATIONS

With the penetration of fuzzy set theory into manufacturing and computer products, applications of fuzzy set theory in power systems are beginning to receive attention from power systems researchers. Fuzzy sets were first introduced in solving power systems long-range decision making problems in [10], about two decades ago.

The growing number of publications on applications of fuzzy set-based approaches to power systems indicates its potential role in solving power systems problems. The results obtained so far are promising but fuzzy set theory is not widely accepted. The reasons for its lack of acceptance include: misunderstanding of the concept, excessive claims of some researchers, lack of implemented and available systems, and its status as a new theory. With the advance of fuzzy set theory and the achievements made in applications to other areas, it is beginning to receive power researchers attention and it is felt that there is a need to develop more information on this subject [11].

Fuzzy logic system estimates functions from sample data. It is a model free estimator, which estimates a function without requiring a mathematical description of how the output functionally depends on the input. It learns the model only from samples. It is a model free estimator, which estimates a function without requiring a mathematical description of how the output functionally depends on the input. It learns the model only from samples.

A fuzzy set \( F \) in a universe \( U \) is characterized by a membership function \( \mu_F \) which takes values in the interval \([0,1]\) namely, \( \mu_F : U \rightarrow [0,1] \). Thus a fuzzy set \( F \) in \( U \) is represented as a set of ordered pairs of generic element \( u \) and its grade of membership function:

\[
F = \{(u, \mu_F(u))|u \in U\}
\]

Let \( A \) and \( B \) be two fuzzy sets in \( U \) with membership function \( \mu_A \) and \( \mu_B \) respectively. The fuzzy set operations of union, intersection and complement for fuzzy sets are defined via their membership functions.

**Union:** The membership function \( \mu_{A \cup B} \) of the union \( A \cup B \) is pointwise defined for all \( u \in U \) by

\[
\mu_{A \cup B}(u) = \max \{ \mu_A(u), \mu_B(u) \}
\]

**Intersection:** The membership function \( \mu_{A \cap B} \) of the union \( A \cap B \) is pointwise defined for all \( u \in U \) by

\[
\mu_{A \cap B}(u) = \min \{ \mu_A(u), \mu_B(u) \}
\]

**Complement:** The membership function \( \mu_A \) of the complement of a fuzzy set \( A \) is pointwise defined for all \( u \in U \) by

\[
\mu_A(u) = 1 - \mu_A(u)
\]

The components of conventional and fuzzy systems are quite alike, differing mainly in that fuzzy system contain “fuzzifiers” which convert inputs to their fuzzy representations, and “defuzzifiers” which convert the output of the fuzzy process logic into “crisp” (numerically precise) solution variables.

The basic configuration of fuzzy logic control or classifier system is shown in Fig. (1) and described in the following.

*Fig. (1) Fuzzy Logic Operation*

The fuzzification interface measures the values of input variables and then converts input data into suitable linguistic values which may be viewed as label of fuzzy sets.

The knowledge base comprises knowledge of the application domain and the attendant control goals. It consists of a “data base” and a “linguistic fuzzy control rule base”. The database provides necessary definitions, which are used to define linguistic control rules and fuzzy data manipulation. The rule base characterizes the control goals and control policy by means of a set of linguistic control rules.

The decision-making logic is the core of the operation. It has the capability of simulating human decision-making based on fuzzy logic concepts and the capability of inferring fuzzy control actions employing fuzzy implication and the rules of inference in fuzzy logic. The inference mechanisms
in the fuzzy operation are generally much simpler than those used in a typical expert system. There are two principal methods of inference in fuzzy systems: The Min-Max method and the fuzzy additive method.

Defuzzification is the final phase of fuzzy reasoning. The defuzzification interface converts the range of values of output variables to yield a non-fuzzy control action. Defuzzification uses the centroid or center of gravity technique to find the “balance” point of the solution by calculating the weighted mean of the fuzzy region. For fuzzy solution \( A \), the centroid is formulated as follows:

\[
c . o . g = \frac{\sum_{i=0}^{n} d_i \mu_A (d_i)}{\sum_{i=0}^{n} \mu_A (d_i)}
\]

where \( d \) is the \( i \)th domain value and \( \mu_A(d_i) \) is the truth membership value for that domain point [12,13].

3. APPLICATION OF FUZZY CONCEPTS TO TRANSIENT STABILITY

In this section, the method and the procedures for application of the fuzzy concepts to the transient stability problem are described. The example system under study is the IEEE nine bus, three generators standard test power system. A one-line diagram for the system is shown in Fig. (2), and the system characteristics are given in [14].

![Fig. (2) - Power system under study](image)

3.1 Generation of Samples

It is assumed that the loads are randomly distributed and they have a normal distribution shape with the following means:

\[
\{ P_A, P_B, P_C \} = \{ 1.25, 0.9, 1.0 \} \text{ p.u.}
\]

For load flow analysis, Bus 1 is taken as the swing bus and Buses 2 and 3 are voltage controlled buses with voltage magnitude of 1.025 p.u. For each load sample, the loading of the generators is determined by economical dispatch of the total load among generators, followed by a load flow analysis. A three phase short circuit is assumed to occur at one line very close to one of the buses of the system and the fault is removed by tripping out the faulted line. The Runge-Kutta numerical integration approach is applied to find the class of each sample. A sample is classified as unstable if the rotor angle of the critical generator which is chosen to be \( G_3 \) reaches 180 degrees within one second [4], otherwise the sample is classified as stable.

Generation of samples is performed by changing both the fault location and loading conditions of the system prior to the occurrence of the fault. For this study, a group of samples is generated at six different fault locations with three different load levels (1.6, 1.0, 0.4) p.u. for each of the three loads of the power network under study resulting in 162 samples.

Number of stable samples = 146 (90 %).
Number of unstable samples = 16 (10 %).

In order to improve the classification performance, a normalization process is performed to all the variables of the training set.

3.2 Selection of Most Important Variables

Upon occurrence of a fault in a power system, the balance of power generation and power consumption is disturbed. Normally, there would be an excess of power, and this would reflect in an imbalance in receipt and supply of power in each synchronous machine. The deviation would then accelerate or decelerate the generator rotors, which results in the deviation of rotor speeds relative to each other. The signal that can detect the imbalance in power is the angular acceleration of the rotor. Hence, it is helpful to choose the acceleration and speed at the instant of major disturbances, as input features for the proposed fuzzy classifier system. In accordance with the previous intuition, three features are chosen using the Single Ranking method based on previous experience of applying a pattern recognition technique to the same problem [4]. The first is the prefault loading of the generator or the mechanical input power \( P_m. \) It is known that the higher the loading of generator, the higher the risk of instability. The second feature is the generator kinetic energy deviation \( K.E \) or \( 0.5 \text{ M \omega}^2 \) at \( t = T_{cl}^+ \). The third feature is the average acceleration during fault \( \alpha_{av} \). It is the average value of the two rotor angular accelerations \( \alpha_1 \) at \( t = T_f^+ \), and \( \alpha_2 \) at \( t = T_{cl}^+ \). \( T_f \) is the instant of fault and \( T_{cl} \) is the instant of fault clearing. \( P_m \) is a direct outcome of the load flow results. The other two features are determined from a transient stability study using the second-order model of the machine.
Full details of the reasons for choosing these features are mentioned in [4].

3.3 Generation of Fuzzy Rules

The procedure of generating fuzzy rules consists of two phases: partitioning the pattern space into fuzzy subspaces, then inducing a fuzzy rule for each subspace. So, the three previous variables, which are the inputs of the proposed fuzzy system, are divided as subsets as follows:

1. Loading condition or mechanical input power of the machine (Light, Normal, Heavy).
2. Kinetic Energy deviation of the generator at the instant of fault clearing (Low, High).
3. Average acceleration of machine (Very Small, Small, Medium, Large, Very Large).

The fuzzy subsets of the three normalized input variables relations against their degrees of membership are shown in Figs. (3), (4) and (5).

After generating the training set, two different schemes can be designed using the proposed fuzzy classification technique. The first scheme uses the three input variables as follows: \( (P_m : 3 \text{ subsets}, \ K.E : 2 \text{ subsets}, \ \alpha_{av} : 3 \text{ subsets} ) \). The simulation results are used as the database to build the rule-base of the fuzzy classifier system. Tables (1) and (2) explain the rule base for the stability classification of the training set using the first fuzzy classifier scheme.

### Table (1) – Rule base of the first scheme (K.E is low)

<table>
<thead>
<tr>
<th>( \alpha_{av} )</th>
<th>( P_m )</th>
<th>Light</th>
<th>Normal</th>
<th>Heavy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>Stable</td>
<td>Stable</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>Stable</td>
<td>Stable</td>
<td>Stable</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>---</td>
<td>Unstable</td>
<td>Unstable</td>
<td></td>
</tr>
</tbody>
</table>

### Table (2) - Rule base of the first scheme (K.E is High)

<table>
<thead>
<tr>
<th>( \alpha_{av} )</th>
<th>( P_m )</th>
<th>Light</th>
<th>Normal</th>
<th>Heavy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>---</td>
<td>Stable</td>
<td>Stable</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>---</td>
<td>Unstable</td>
<td>Unstable</td>
<td></td>
</tr>
</tbody>
</table>

Using the samples of the training set, the previous scheme presents an unacceptable classification performance. Six of the sixteen unstable samples are classified as stable with a high misclassification percentage (37.5%). Also, it is concluded from Tables (1) and (2) the insignificance effect of the kinetic energy as an effective feature. So, the second scheme is designed as follows: \( (P_m : 3 \text{ subsets}, \ \alpha_{av} : 5 \text{ subsets} ) \). Table (3) shows the rule base for the stability classification of the training set using the second fuzzy classifier scheme.

### Table (3) – Rule base of the second scheme

<table>
<thead>
<tr>
<th>( \alpha_{av} )</th>
<th>( P_m )</th>
<th>Light</th>
<th>Normal</th>
<th>Heavy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Small</td>
<td>Stable</td>
<td>Stable</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>Stable</td>
<td>Stable</td>
<td>Stable</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>---</td>
<td>Stable</td>
<td>Stable</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>---</td>
<td>Unstable</td>
<td>Unstable</td>
<td></td>
</tr>
<tr>
<td>Very Large</td>
<td>---</td>
<td>---</td>
<td>Unstable</td>
<td></td>
</tr>
</tbody>
</table>

The classification performance of the second fuzzy logic classifier was very good. The total number of misclassified samples were 2 out of 162 and all the unstable samples are correctly classified. In order to test the proposed fuzzy classifier system, a test set comprising of 384 samples was generated by the same way as the training set. Table (4) shows the performance of the two different fuzzy classifier schemes using both the training and test sets.
and comparable correct classification performance. This scheme reveals simplicity, speed and comparable correct classification performance. Compared with other AI approaches used for the same problem, this scheme reveals simplicity, speed and comparable correct classification performance. The author has presented different AI techniques for solving the TSA problem [4-6] beside the work in this paper. It is concluded that the correct classification percentage is almost the same for the different schemes (ranging from 98-99%). The common advantages of all the AI techniques used are:

1- They do not need prior knowledge of the system and/or any mathematical model of the machines.
2- The prediction of the transient stability in real time is based on simple computation.
3- These schemes are inherently adaptive since they are trained using different fault locations and load levels.

The difficulty in designing the classifier may limit the use of the Pattern Recognition technique. This scheme is characterized rather than the Pattern Recognition and Neural Networks methodologies by its simplicity since it used just only two features \((P_m, \alpha_m)\). Consequently, it is just needed to measure the values of the active power of the machine before fault, at the instant of fault inception and at the instant of fault clearing to calculate the two features.

### Table (4) Results of fuzzy classification based schemes

<table>
<thead>
<tr>
<th>Fuzzy Scheme Used</th>
<th>Misclassified training patterns (out of 162)</th>
<th>Misclassified testing patterns (out of 384)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheme (1) ((P_m: 3 \text{ subsets, } K.E: 2 \text{ subsets, } \alpha_m: 3 \text{ subsets}))</td>
<td>6/16 unstable, 37.5%</td>
<td>4/40 unstable, 10%</td>
</tr>
<tr>
<td></td>
<td>0/146 stable, 0%</td>
<td>8/344 stable, 2.3%</td>
</tr>
<tr>
<td></td>
<td>6/162 total, 3.7%</td>
<td>12/384 total, 3.5%</td>
</tr>
<tr>
<td>Scheme (2) ((P_m: 3 \text{ subsets, } \alpha_m: 5 \text{ subsets}))</td>
<td>0/16 unstable, 0%</td>
<td>1/40 unstable, 2.5%</td>
</tr>
<tr>
<td></td>
<td>2/146 stable, 1.4%</td>
<td>3/344 stable, 0.8%</td>
</tr>
<tr>
<td></td>
<td>2/162 total, 1.2%</td>
<td>4/384 total, 1.04%</td>
</tr>
</tbody>
</table>

### 3.4 Discussion

The author has presented different AI techniques for solving the TSA problem [4-6] beside the work in this paper. It is concluded that the correct classification percentage is almost the same for the different schemes (ranging from 98-99%). The common advantages of all the AI techniques used are:

1- They do not need prior knowledge of the system and/or any mathematical model of the machines.
2- The prediction of the transient stability in real time is based on simple computation.
3- These schemes are inherently adaptive since they are trained using different fault locations and load levels.

The difficulty in designing the classifier may limit the use of the Pattern Recognition technique. This scheme is characterized rather than the Pattern Recognition and Neural Networks methodologies by its simplicity since it used just only two features \((P_m, \alpha_m)\). Consequently, it is just needed to measure the values of the active power of the machine before fault, at the instant of fault inception and at the instant of fault clearing to calculate the two features.

### 4. CONCLUSION

A fuzzy rule-based classifier system is developed for transient stability assessment of a multi-machine power system. The degree of accuracy is high and computation is fast enough for the program to be used for on-line transient stability assessment. Compared with other AI approaches used for the same problem, this scheme reveals simplicity, speed and comparable correct classification performance.

### 5. REFERENCES