PROSPECTIVE USE OF FUZZY LOGIC IN POWER SYSTEM RELIABILITY

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ABSTRACT

Power system reliability calculations involving generation only are referred to as Hierarchical Level 1 (HL1). Power system reliability calculations involving both generation and transmission systems are referred to as Hierarchical Level 2 (HL2), and also as composite system reliability. Since the inception of probabilistic HL1 studies, a significant knowledge base has been built up through the study of a fairly large number of systems reported in the literature. Based on the information available to an expert from experience and from the available literature, it may be possible to construct a basic knowledge base for reliability and to evaluate any particular system condition as a variation. Fuzzy sets and fuzzy logic may provide an alternative for handling the uncertainty that might be associated with an HL1 study.

KEYWORDS: HL1 Reliability, Fuzzy sets, Fuzzy logic.

1.0 INTRODUCTION

Most early reliability studies for power systems were carried out by using deterministic techniques. It was the uncertainty about generating unit availability and load patterns, and the need to quantify the availability through forced outage rates, that gave rise to the development of probabilistic techniques. The probabilistic approach started to emerge as early as 1930. Having experienced different kinds of units for comparably long periods of time and under diverse operating conditions, it has been possible to establish the basis for probabilistic studies. Two basic approaches for probabilistic techniques have been widely implemented, the State Enumeration approach and the Monte Carlo approach. Both give as an output well defined indices which make sense from the engineering point of view. The major output indices are Loss of Load Expectation LOLE, and Expected Energy Not Served EENS. The merit in applying probabilistic techniques is the simulation of random outages likely to happen for any of the system components. There has been undeniable success for probability as quantifying the reliability study on a rational basis. The probability logic handles one sort of uncertainty, which is the random outage of system units. The fuzzy logic handles the uncertainty represented by imprecision and ambiguity. It is believed that the fuzzy logic may have a role to play in reliability studies either exclusively or inclusively with probability theory. Developing a fuzzy algorithm for static or dynamic system reserve, possibilistic modelling as opposed to probabilistic modelling for system components, and developing inference techniques to assess the probabilistic reliability criteria are just examples of prospective applications. This paper deals with the last point. It develops a fuzzy logic inference technique for the probabilistic criterion LOLE as the loading level, number of units and unit size are considered.

2.0 FUZZY SETS AND FUZZY LOGIC

The mathematical basis of fuzzy sets was developed by L. Zadeh in 1965 [1]. The concept of a computational model for the semantics was introduced in a pioneering paper by Zadeh in 1973 [2]. Linguistic variables, fuzzy conditional statements and fuzzy algorithms have been explained thoroughly in this paper. Only one year after, the first real world application of fuzzy logic was the fuzzy logic controller introduced by Mamdani [3]. Although the control realm was never thought before to be an area of application, the pioneering work by Mamdani consolidated the power of fuzzy logic theory. Implementations of fuzzy logic controllers are presented in Mamdani and Lee [4,5,6]. Because of its ability to quantify the human reasoning approach, it is not uncommon nowadays to detect real applications of fuzzy logic controller ranging from water shower control to automatic suburban electric trains [7]. Although there are available a tremendous number of publications in fuzzy sets and fuzzy logic, we devote the following section to present an overview that leads into fuzzy logic.

2.1 Fuzzy Set

Every fuzzy set is characterized by its own membership...
grade function that maps each element over the universe of discourse to a corresponding real number in the interval [0 1]. This number represents the grade of membership for such an element in the concerned fuzzy set or sometimes referred as the degree of complying of the individual with the fuzzy restriction defined over the discourse. The most commonly used is the linear membership grade function. Figure 1 shows a linear membership grade function.

\[
\mu(u,a,b,c,d) = \begin{cases} 
0 & \text{if } (a-c) > u \\
\frac{u-(a-c)}{c} & \text{if } (a-c) \leq u < a \\
1 & \text{if } a \leq u < b \\
\frac{(b+d)-u}{d} & \text{if } b \leq u \leq (b+d) \\
0 & \text{if } (b+d) < u 
\end{cases}
\]

![Figure 1 A Linear Membership Grade Function](image)

2.3 Compositional Rule Of Inference

Semantically, if we have a rule such as "IF X is SMALL then Y is BIG" and we have an information that X is SMALL, it is unquestionable to infer that Y is BIG. Even with X assigned a modified rather than an atomic linguistic term, the inference process provides a modified output for Y. This logical process is named modus ponens MP. However if the information was given about Y and we can infer backward about X, such inference process is called modus tollens MT.

It should be clear that MP is a forward or data driven inference technique, while MT is backward one. This makes the MP more convenient in design and planning applications, whereas the MT is more suitable for diagnostic applications. The computational model for this logic is referred as rule composition:

\[
Y = X \cdot R = \bigvee x (\mu_A (x) \land \mu_R (x, y))
\]

This resembles matrix multiplication but with max-min operators.

For real systems several conditional statements, or rules, usually govern the inference process. Every rule is supposed to have its fuzzy relation R and the equivalent fuzzy relation for the entire system is R where:

\[
R = (R_1 \lor R_2 \ldots \lor R_n)
\]

A significant simplification in the process could be attained when the input data X is a crisp singleton rather than a fuzzy set. In such a case, the inferred value of Y can be read off the fuzzy relational matrix and the whole inference process is summarized then in two main steps Fuzzification and Defuzzification.

3.0 FUZZY LOGIC INFERENCE FOR HL1 RELIABILITY

3.1 Problem identification

It is unquestionable that LOLE represents one of the most usable criterion for power system reliability.
The factors which influence generation - only reliability calculations are well known. They are as follows.

a. System peak load
b. Size of units
c. Number of units
d. Forced outage rates of units
e. Load factor, or the relative energy content of the load.
f. Maintenance

A decision was made to examine the LOLE in hours per year as influenced only by the System Ratio SR, which is the ratio of Peak Load to Installed Capacity in the system, and the Average Unit Size AUS. The AUS can combine the second and third factors mentioned above. Since the purpose of this paper is not to introduce a comprehensive study but rather to tackle the subject, the other factors were ignored.

It is one thing to use System Ratio and Average Unit Size to infer something about Loss of Load Expectation. It is another matter, and process, to quantify the inference. The manner of quantifying the inference is through the use of fuzzy sets and fuzzy logic as demonstrated below.

3.2 Development Of Membership Grade Functions And Inference Strategy

The membership grade functions and the inference strategy are usually drawn from the knowledge available from experts, and global system characteristics. In our case, since we are dealing with a probabilistically computed value, we would get the knowledge from the literature available that presents studies of diverse system structures.

Watchorn [8] was an early pioneer in developing probabilistic methods for the analysis of power system reliability. In a 1957 paper, he examined the difference in values of LOLE versus Annual Peak Load for generation combinations ranging from 180 - 50 MW units to 45 - 200 MW units, and finally to 15 - 600 MW units. As expected, the combination of 180 - 50 MW units was the most reliable. While his objective was to examine the reliability of many smaller units relative to a few larger units, it is an important fact that he started the development of a knowledge base.

In a 1974 paper [9], Billinton, Jain and McGowan examined a test system consisting of 75 generating units with a total installed capacity of 10,100 MW. To indicate the range of units, there were 10 - 25 MW units each with a Forced Outage Rate of 0.005, 8 - 200 MW units each with a FOR of 0.04, and finally 5 - 500 MW units each with a FOR of 0.07. In that analysis they successively added 650 MW units to the system and looked at the resultant influence on LOLE in days per year as a function of System Peak Load in MW. While their intent was to examine the effect of partial representation in generation planning studies, nevertheless they contributed significantly to the knowledge base.

Allan and Musa [10] looked at the modelling methods aspects of reliability evaluation of generating systems. In fact, they considered the usual recursive method, a Fast Fourier Transform method, a Cumulant method and the Normal Distribution method. One of the very interesting things that they did was to plot the LOLE in days per year against the ratio of Peak Load to Installed Capacity for each of the methods which they used. For purposes of this paper, this ratio will be called the System Ratio. While their objective was to compare modelling computational methodologies, they also contributed significantly to the knowledge base.

Figure 2 shows a plot of data taken from a paper by Watchorn [8] and from publications by Billinton [9].

As expected, this is a scatter diagram because it includes data which has widely varying values of all
the factors mentioned in Section 3.1 above. The data from Watchorn involved identical units, a peak load lasting all hours of the year, and a low forced outage rate of 0.02. The data from Billinton is for a system with units of widely varying capacities, a more usual load curve, and more realistic forced outage rates. When these considerations are made, the trend line of Watchorn and that of Billinton are quite similar.

The figure shows that it may be possible to establish groups of fuzzy subsets over a proper universe of discourse for each of the factors involved. With the fuzzy sets having been defined, they can be processed through the fuzzy rule base for inference to infer LOLE values under given circumstances. A typical rule may look like:

IF SR IS A AND AUS IS B THEN LOLE IS C

where A, B and C are corresponding fuzzy subsets for SR, AUS and LOLE. Technically, the left hand side factors in the rule are termed antecedents whereas the right hand side are the consequent.

Table I shows the selected fuzzy sets of every factor. The corresponding universe of discourses are:

<table>
<thead>
<tr>
<th>SR</th>
<th>AUS</th>
<th>LOLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>.66 .80%</td>
<td>[0 600] MW</td>
<td>[1 251] hr/yr</td>
</tr>
</tbody>
</table>

For the linearly proportional characteristics of the membership grade function, it becomes more convenient to use a logarithmic scale for the LOLE on the interval [0 2.4].

Table 2 Inference Table

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<th>Table 2 Inference Table</th>
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</table>

4.0 FUZZY LOGIC INFERENCE MECHANISM

Computationally, the system equivalent fuzzy relation is obtained by union of the individual relations. According to rule composition for inference, the overall fuzzy relation for the system which is obtained from the union operation of the individuals is composed through min-max operators with the antecedent fuzzy sets. Another alternative is easier in implementation if the input is a crisp singleton [4]. This procedure can be summarized in the following steps.

4.1 Fuzzification

Fuzzification is the process of assigning the input singleton a membership grade in all corresponding fuzzy sets defined for such an antecedent over the entire rule base. The same is done for every antecedent input. The minimum membership grade amongst the input antecedents is selected. Scaling with the minimum membership grade, rather than minimum operation, is performed on the individual consequent fuzzy set for each rule. The preference of scaling is to avoid discontinuity in the inferred values. The consequent universe of discourse is discretized. The maximum scaled membership grade for every discrete element over the entire set of rules is selected. This constitutes a fuzzy output for the consequent. It is very useful to give a concrete example of the mechanical steps taken in applying the inference process. Figure 3 shows a diagram which illustrates the process of fuzzifying two crisp sets for SR at 78% or 0.78 and AUS at 400 MW over the fuzzy rule base.

Table 1 Fuzzy Set Definition for SR, AUS, LOLE

<table>
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<tr>
<th>Table 1 Fuzzy Set Definition for SR, AUS, LOLE</th>
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It is one thing, in building a fuzzy logic inference process, to design the fuzzy subsets amenable for each factor. It is another thing to determine the relative importance of each antecedent to the consequent. In other words, to construct the fuzzy rule base. It is important to mention that for satisfactory results, trial and error is performed over a wide range in the design of both fuzzy sets and the rule base. With the assigned classes of membership grades in Table 1 and through a trial and error process, the best rule structure as far as this paper is concerned is presented in Table 2.
Figure 3 Fuzzification Mechanism
4.2 Defuzzification

Defuzzification is the process of extracting a crisp value as representative of a fuzzy set. The output histogram, which is the consequent output fuzzy set, should be defuzzified to get a singleton LOLE value. Different techniques generally used are mean of maxima MOM and centre of area COA. COA shows superior results because it weights every discrete element rather than only those of maximum membership grades.

![Table 3 Sample Results](image)

<table>
<thead>
<tr>
<th>AUS (MW)</th>
<th>100</th>
<th>200</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR</td>
<td>Watchorn</td>
<td>Fuzzy Logic</td>
<td>Watchorn</td>
<td>Fuzzy Logic</td>
<td>Watchorn</td>
<td>Fuzzy Logic</td>
</tr>
<tr>
<td>70</td>
<td>&lt;1</td>
<td>1.92</td>
<td>&lt;1</td>
<td>1.92</td>
<td>1.925</td>
<td>1.0</td>
</tr>
<tr>
<td>74</td>
<td>&lt;1</td>
<td>1.92</td>
<td>&lt;1</td>
<td>1.92</td>
<td>2.4</td>
<td>1.925</td>
</tr>
<tr>
<td>78</td>
<td>31.6</td>
<td>33.6</td>
<td>31.6</td>
<td>33.6</td>
<td>5.0</td>
<td>54.69</td>
</tr>
<tr>
<td>80</td>
<td>28.88</td>
<td>39.5</td>
<td>43.65</td>
<td>39.5</td>
<td>68.12</td>
<td>52.08</td>
</tr>
</tbody>
</table>

Table 3 Sample Results

A singleton representative using COA is obtained by:

$$U = \frac{1}{N} \sum_{i=1}^{N} \mu_i u_i$$

where:

- $N$ = number of discrete elements over the universe of discourse
- $u_i$ = discrete element $i$
- $\mu(u_i)$ = corresponding membership grade for discrete element $i$

Figure 4 shows a block diagram representation for the crisp input-crisp output inference process.

5.0 SAMPLE CASE STUDY RESULTS

Various runs for the program were executed to investigate the effect of the peak load percentage and the average unit size simultaneously. The given set of results in Table 3 is rationally susceptible to the membership grade function parameters as well as the individual rule structure. Both are considered the tuning up tools for the fuzzy logic inference process. It, however, becomes much easier if the fuzzy sets for the different factors were established invariantly. The more expertise and statistics employed for building rule structures and defining the membership grade function, the more accurate results are anticipated. Table 3 depicts the results of studying the system of the Watchorn paper for various conditions of SR and AUS. The results show a comparison of the Watchorn results and the results obtained from the fuzzy logic process described in this paper.

It is important to state what the application of fuzzy logic to power system reliability is not, and what it is. The application of fuzzy logic is not curve fitting, nor is it regeneration of numerical results as such. Rather it is the process of establishing a system of inference in the presence of uncertainty.

Referring to the results presented in Table 3, it is noticed that:

![Figure 4 Fuzzy Logic Inference Process](image)
(a) There is not always perfect numerical coincidence between the Watchorn results and the fuzzy logic results.

(b) Both sets of results have the same general trend as the System Ratio goes higher.

Item (a) may be conceived negatively. However in establishing the results on a linguistic basis, a numerical value of LOLE of 2.4 hours/year might be just as "good" as a numerical value of LOLE of 1.9 hours/year. They both may be belonging to the same $\alpha$-cut set in the "good" fuzzy set. In the same context, a numerical value of LOLE of 14 hours/year might be just as "poor" as a numerical value of LOLE of 28 hours/year. In other words in judging performance results based on linguistic criteria the consistency of being in the same range, or of having the same kind of closeness, is of most importance. As pointed out in item (b) this same kind of closeness is quite evident in the results presented, especially as the System Ratio goes higher.

The system characteristics as modeled by linguistic variables can be brought closer to reality as more effort is made in tuning the linguistic terms, and in the rule base construction. The fuzzy logic technique for reliability assessment could be helpful for inferring the reliability index when the input data undergoes some sort of uncertainty.

6.0 CONCLUSIONS

The intent of this study was to examine the possibility of using fuzzy logic for determining HLI reliability levels. The factors chosen as representing a suitable influence on Loss of Load Expectation were System Ratio and Average Unit Size. This is clearly a very coarse representation and yet the results are quite good. Further work, to include Forced Outage Rates and Load Shape by simulating their uncertainty using fuzzy set theory, represents the next stage of the study.

7.0 REFERENCES