Chapter 5
Risk Assessment for Power Distribution Network

The main objective of electric power delivery business is to supply an electric power to end consumers with an appropriate reliability and quality of power supplied, at the same time balancing benefits of all stakeholders. The power distribution network, on the other hand, has to be designed, constructed, operated and maintained in such a way that providing targeted reliability and quality whilst creating minimal adverse impacts to stakeholders. Although there are several dimensions of risk involved in power delivery business [3, 97], the most crucial risk component that affects the power consumers is the power system performance in terms of the power system reliability and quality.

The terms “risk” and “reliability” may not have the same meaning but they provide the identical implication. Higher risk means lower reliability and vice versa. Several studies have examined the topic of reliability assessment using historical data as a basis for calculation the expected reliability of distribution circuits [98, 99, 100]. This methods is widely used, but it has the drawback of the data may not readily available or accurate. Also, the approach is reactive in the sense that utility waits for the problems to occur and bases the necessity for improvement on the past performance. The use of fuzzy logic can overcome the obstacle of scarce, vague and imprecise of data because the process is very close to the problem solving method of human being which is universally accepted for handling this kind of problem. Furthermore, the use of Markov chain makes it possible to predict the risk potential at any time instance along the asset life. It thus makes the asset manager able to proactively reinforce the distribution networks beforehand instead of waiting for them to fail. The reliability of distribution network can then be secured.

As already discussed in details on formulating the asset categorization in chapter 4, the distribution network comprises of many power equipment such as cables, wires, switches, poles and hardwares, ducts, etc. It is operated in diverse environment; in terms of economic perspective, the operational environment includes urban commercialized area, suburban residential neighborhood, or industrial estate complex; in terms of harmfulness to network, it may be categorized into highways, local roads, bushes, agricultural fields, polluted locations, coastal area or construction sites. Since the distribution network connects the end users to the electric power, the failures of the network result in power blackout or outage to customers. The failures of distribution network depend primarily on the design, operation and maintenance of the distribution network. This chapter addresses the problems of power system failure, i.e. what causes the failure in particular. In order to determine the possibility that the distribution system would fail, the network asset conditions must be first determined; manipulate these asset condition with the operational and external environment, the likelihood of the network failure would then be quantified. The main technique applied for determining both asset condition and network failure possibility is the Fuzzy rule based evaluation. In addition, the Markov chain is also employed to predict the future condition, given the transitional probability matrix of deterioration rate.

5.1 Chapter Overview

The chapter begins with theoretical background of fuzzy logic and further discusses on fuzzy inference system and its application. Then the discussion turns to the principle of Markov chain and its application. In the third section, the application of fuzzy logic and Markov chain in determining risk possibility of distribution network failure will be thoroughly examined; it is begun by trying to quantify network component condition rating either at present or future stage, followed by conceptualizing fuzzy linguistic variables of network property and stressors in or that the possibility of network failure can be brought about at the final stage.

5.2 Fuzzy Logic

The term *fuzzy set* first appeared in 1965 when Professor Lotfi A. Zadeh from the University of Berkeley, USA, published a paper entitled “Fuzzy sets” [101]. Since then he has achieved many major theoretical breakthroughs in this field and has been quickly joined by numerous research workers developing theoretical works. At the same time, some researchers turned their attention to the resolution by fuzzy logic of problems considered to be difficult. In 1975 professor Mamdani from London developed a strategy for process control and published the encouraging results he had obtained for the control of a steam motor. In 1978 the Danish company, F.L. Smidth, achieved the control of a cement kiln. This was the first genuine industrial application of fuzzy logic.

Fuzzy logic began to interest the media at the beginning of the nineties. This technology has achieved impressive success in diverse engineering applications ranging from mass market consumer products to sophisticated decision and control problems [102]. The numerous applications in electrical and electronic household appliances, particularly in Japan, were mainly responsible for such interest. Washing machines not requiring adjustment, camcorders with steady-shot image stabilization and many other innovations brought the term “fuzzy logic” to the attention of a wide public [103]. The usage of Fuzzy logic technology is now widely accepted in many disciplines such as engineering, management, social science, medical sciences, and biological and chemical fields.

Fuzzy logic implements human experiences and preferences via membership functions and fuzzy rules. Heuristics, intuition, expert knowledge, experience, and linguistic descriptions are then obviously important to domain expert. Virtually, there exist some “imprecision” in the problem formulation and subsequent analysis to any practical problems. For example, distribution system planners rely on spatial load forecasting simulation programs to provide information for a variety of planning scenarios [104]. Linguistic descriptions of growth patterns, such as close by or fast, and design objectives, such as, prefer or reduce, are imprecise in nature. The conventional determination approaches do not capture such linguistic and heuristic knowledge in an effective manner.

The advantage of Fuzzy technique is twofold: the emulation of human problem solving and its immunity to imprecise data. Human uses linguistic terms to quantify the data they have encountered such as fast speed, near obstacle, slippery road, etc. They then solve or react to the problem encountered by using what they have already known or experienced in that area. The actions taken for previous case might be pumping (pressing and releasing alternately) the car brake hardly and quickly in order to get the car stopped without accident.

5.2.1 Basic Fuzzy Logic Theory

In this section the theoretical principle of Fuzzy sets theory and Fuzzy logic will be discussed. As well, the practical example would also be shown.

Fuzzy logic is a scientific tool that permits modeling of system without detailed mathematical descriptions using qualitative as well as quantitative data [105]. Linguistic terms are used to approximate the amount or quality of data. To gain more understanding of fuzzy logic concept, figure 5.1 provides a pictorial description on the temperature classifications where MF represents the classification belonging (Membership Function). If people want to classify the climate as cold and hot, what should the boundaries for the segregation? This question might be difficult to answer in reality. In fact, the transition from cold to hot temperature (or vice versa) occurs in a gradual manner instead of abrupt change (figure 5.1(a)). It is thus that there is no exact boundary to segregate these two classes.

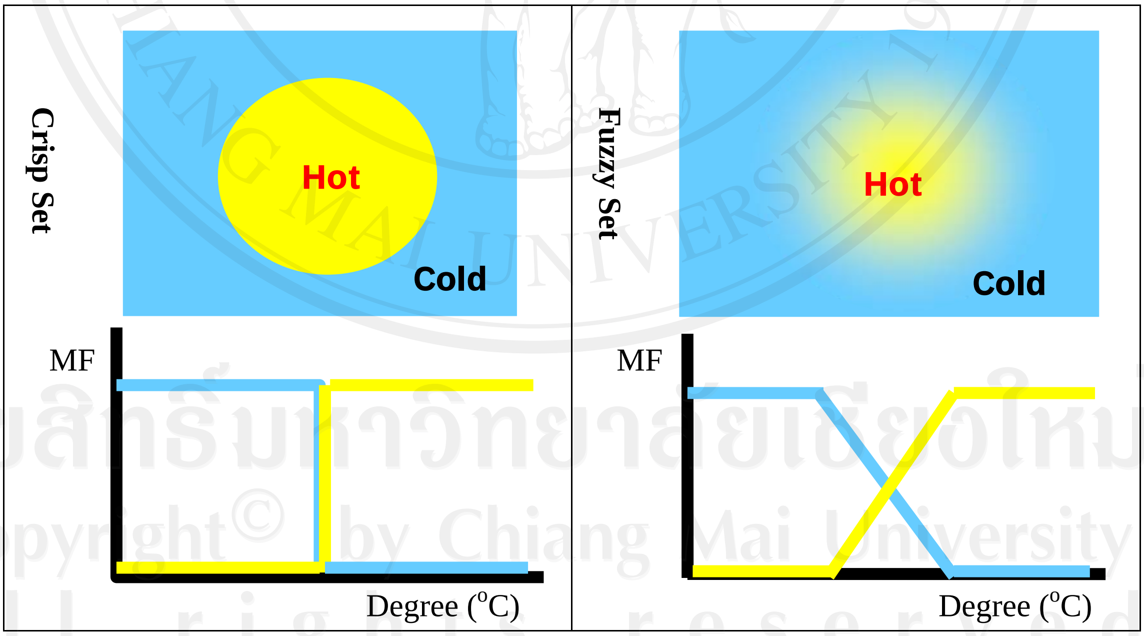


Figure 5.1 Fuzzy sets on climate temperature

Mathematical foundation of Fuzzy logic is explained in the following subsections [47, 104, 106, 107, 108, 109].

Linguistic Variables

Fuzzy logic is primarily concerned with quantifying and reasoning about vague or fuzzy terms that appear in natural language. In fuzzy logic, these terms are referred to as *linguistic variables* or *fuzzy variables*. For example, in the statement "Weather is hot" it is implied that the linguistic variable *temperature* has the linguistic value of *hot*. Table 5.1 shows other examples of linguistic variables and typical linguistic values that might be assigned to them.

Table 5.1 Examples of linguistic variables with typical linguistic values

linguistic variables	**linguistic values**
temperature	cold, warm, hot
pressure	low, medium high
speed	slow, creeping, fast
height	short, medium, tall

Linguistic variable like: tall person, hot weather or old machine, 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 decision making process. Fuzzy logic is justified because [104] it is tolerant of imprecisely defined data; it can model non-linear functions of arbitrary complexity; and it is able to build on top of the experience of expert.

In fuzzy logic system, the linguistic variables are used in fuzzy rules. A Fuzzy rule infers information about a linguistic variable contained in its conclusion (consequence) from information about another linguistic variable in its premise (antecedence). The possible range of a linguistic variable is the *universe of discourse*. For example, in the statement "IF temperature is high THEN risk is high", the phase "temperature is high" and "risk is high" occupied a section of the variable's universe of discourse; it is a fuzzy set.

Fuzzy Set

Let X be the universe of objects with elements x, where A is called a fuzzy subset of X (generally cal fuzzy set). Membership of x in classical set A can be viewed as a characteristic function μ_A from X to (0,1) such that

$$\mu_A(x) = \begin{cases} 1; \, if \;\; x \in A \\ 0; \, if \, x \notin A \end{cases} \tag{5.1}$$

For a fuzzy set A of the universe X, the grade of membership of x in A is defined as:

$$\mu_A(x) \in [0,1] \tag{5.2}$$

where $\mu_A(x)$ is the membership function. The value of $\mu_A(x)$ can be anywhere between 0 and 1, and this range makes it different from a crisp (classical) set. The *closer* the value of $\mu_A(x)$ is to 1.0, the *more* x belongs to A. Thus, fuzzy set has no sharp boundary, e.g. as shown in Fig. 3.1 above. Each of crisp subsets of X can be shown to have a one-on-one correspondence with the characteristic function, and because the membership functions are extensions of the characteristic functions, fuzzy sets are then extensions of crisp sets.

Fuzzy set elements are ordered pairs indicating the value of a set element and the grade of membership, that is

$$A = \{(x, \mu_A(x)) | x \in A\} \tag{5.3}$$

The most common set operators are defined in the followings. For two fuzzy sets A and B, their union operation is defined as:

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \tag{5.4}$$

The intersection is:

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \tag{5.5}$$

And the complement operation is:

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \tag{5.6}$$

It should be pointed out that other operations can be defined, in particular in the t-norm (minimum operator) and t-conorms (maximum operator which also called s-norm classes). In addition, to perform certain mathematical operations, a crisp set (non-fuzzy) may be requires. The following definition of an α−cut can be used to create a family of crisp sets from a given fuzzy set:

$$\mu_A(x) = \begin{cases} 1; \ if \ \ \mu_A(x) \geq \alpha \\ 0; \ otherwise \end{cases} \tag{5.7}$$

The α−cut concept can be used to form a possibilistic confidence band, which is akin to (though not the same as) the probabilistic confidence interval used in traditional statistical methods. This possibilistic confidence band provides a plausible range (or an interval) for the best estimate.

Membership Function

Every element in the universe of discourse is a member of the fuzzy set to some grade, maybe even zero. The set of elements that have a non-zero membership is called the *support* of the fuzzy set. The function that ties a number to each element of the universe is called the membership function.

There are two alternative ways to represent a membership: continuous or discrete. In the continuous form the membership function is a mathematical function. In the discrete form the membership function and the universe are discrete points in a list (vector). Sometimes it can be more convenient with a sampled (discrete) representation. Type of membership functions are illustrated as the followings.

1). Numerical definition (discrete membership functions)

$$A = \sum_{x_i \in X} \mu_A(x_i) \big| x_i \qquad (5.8)$$

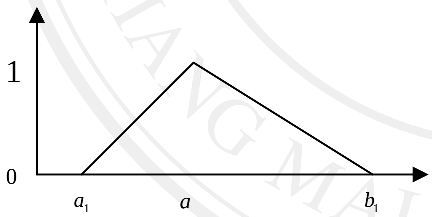
2). Function definition (continuous membership functions) of Gaussian, Triangular and Trapezoid shape.

$$A = \int_X \mu_A(x) \big| x \qquad (5.9)$$

2.1) Gaussian membership function

$$f(x : \sigma, \bar{x}) = e^{-(x-\bar{x})^2 / 2\sigma^2} \qquad (5.10)$$

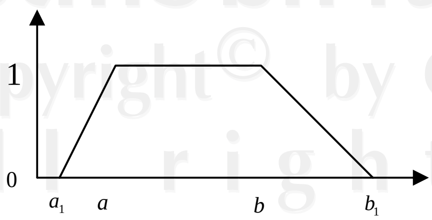
2.2) Triangular membership function



$$\mu_A(x) = \begin{cases} 0 & for\ x \le a_1 \\ \frac{x-a_1}{a-a_1} & for\ a_1 \le x \le a \\ \frac{b_1-x}{b_1-a} & for\ a \le x \le b_1 \\ 0 & for\ b_1 \le x \end{cases}$$

Figure 5.2 Triangular membership function

2.3) Trapezoidal membership function



$$\mu_A(x) = \begin{cases} 0 & for\ x \le a_1 \\ \frac{x-a_1}{a-a_1} & for\ a_1 \le x \le a \\ 1 & for\ a \le x \le b \\ \frac{b_1-x}{b_1-b} & for\ b \le x \le b_1 \\ 0 & for\ b_1 \le x \end{cases}$$

Figure 5.3 Trapezoidal membership function

Fuzzy Logic

In order to gain better understanding of fuzzy logic, a crisp (classical) logic will be first reviewed.

Logical reasoning is the process of combining given proposition into other proposition, and then doing this over and over again. Proposition can be combined in many ways, all of which are derived from three fundamental operations (or connectives): *conjunction*, *disjunction* and *implication*. A proposition, however, has its truth value either true or false. Let p and q are proposition; the three fundamental logic operations can be defined as:

Conjunction

Denoted by $p \wedge q$, is exercised where the simultaneous truth of two separate proposition p and q is asserted. Example of this is "*Load current is High*" AND "*Ambient temperature is High*".

Disjunction

Denoted by $p \vee q$, is exercised where the truth of either or both of two separate proposition p and q is asserted. Example of this is "*Short-circuit current is High*" OR "*Partial discharge is High*".

Implication

Denoted by $p \to q$, usually takes the form of an IF-THEN rule. Example could be IF "*Partial discharge is High*" THEN "*Cable condition is Poor*". The IF part of an implication is called the *antecedent*, whereas the THEN part is called the *consequent*.

In addition to generating proposition using previously described operators, a new proposition can be obtained from a given one by prefixing the clause "*it is false that* …". This is the operation of *negation* (denoted by $\neg p$). Additionally, $p \leftrightarrow q$ is the equivalent relation which means that p and q are both true or false. Table 5.2 illustrates the truth table of five operations of the classical logic.

Table 5.2 Truth table for five operations that are frequently applied to proposition

p	q	$p \wedge q$	$p \vee q$	$p \to q$	$p \leftrightarrow q$	$\neg p$
T	T	T	T	T	T	F
T	F	F	T	F	F	F
F	T	F	T	T	F	T
F	F	F	F	T	T	T

Using the fact (from classical logic manipulation as shown in table 5.3) that $(p \to q) \leftrightarrow \neg[p \wedge (\neg q)]$ and $(p \to q) \leftrightarrow \neg p \vee q)]$, and the equivalent between logic and set theory, the two (non-unique) membership functions for $\mu_{p\to q}(x,y)$ can now be obtained. The first proposition can be shown as:

$$\begin{aligned}\mu_{p\to q}(x,y) &= 1-\mu_{p\cap\bar{q}}(x,y)\\ &= 1-\min[\mu_p(x),1-\mu_q(y)]\end{aligned} \tag{5.11}$$

and the second could be:

$$\begin{aligned}\mu_{p\to q}(x,y) &= \mu_{\bar{p}\cup q}(x,y)\\ &= \max[1-\mu_p(x),\mu_q(y)]\end{aligned} \tag{5.12}$$

Table 5.3 Proof of $(p\to q)\leftrightarrow\neg[p\wedge(\neg q)]$

p	q	$p\to q$	$\neg q$	$p\wedge\neg q$	$\neg(p\wedge\neg q)$	$\neg p$	$\neg p\vee q$
T	*T*	*T*	*F*	*F*	*T*	*F*	*T*
T	*F*	*F*	*T*	*T*	*F*	*F*	*F*
F	*T*	*T*	*F*	*F*	*T*	*T*	*T*
F	*F*	*T*	*T*	*F*	*T*	*T*	*T*

Table 5.4 Validation of equation (5.11) and (5.12)

$\mu_P(x)$	$\mu_q(y)$	$1-\mu_P(x)$	$1-\mu_q(y)$	$\mathbf{max}[1\mu_P(x),\mu_q(y)$	$1-\mathbf{min}[\mu_P(x),1-\mu_q(y)]$
1	1	0	0	1	1
1	0	0	1	0	0
0	1	1	0	1	1
0	0	1	1	1	1

One thing to keep in mind is that in classical logic a proposition is either *true* or *false*, but not both. The *truth* or *falsity* which is assigned to a statement is its *truth-value*. In fuzzy logic a proposition may be true or false or have an intermediate truth-value, such as *possibly*. The sentence "*the weather is hot*" is an example of such a proposition in a fuzzy system. It may be convenient if the possible truth values are restricted to a discrete domain, for example {0, 0.5, 1} for false, possibly true and true; which leads to the multi-valued logic. In practice a finer subdivision of the unit interval may be more appropriate. From table 5.2 above, similar truth-tables can be also made in fuzzy logic. If for example staring out by defining *negation* and *conjunction*, then the other truth-tables can be derived from that. Let assume that negation is defined as the set theoretic complement, i.e. $not\ p\equiv 1-p$, and that disjunction is equivalent to set theoretic union, i.e. $p\vee q\equiv\mathbf{max}(p,q)$. And using theoretic set operation, then truth-tables for *or*, *nor*, *nand* and *and* can be found for instance as table 5.5:

Table 5.5 Mulit-valued logic operation

OR
$(p \vee q)$

0	0.5	1
0.5	0.5	1
1	1	1

NOR
$\neg(p \vee q)$

1	0.5	0
0.5	0.5	0
0	0	0

NAND
$\neg p \vee \neg q)$

1	1	1
1	0.5	0.5
1	0.5	0

AND
$\neg(\neg p \vee \neg q)$

0	0	0
0	0.5	0.5
0	0.5	1

The two rightmost tables are negations of left hand tables, and the bottom tables are reflections along the anti-diagonal (orthogonal to the main diagonal) of the top tables. It is comforting to realize that even though the truth-table for *and* is derived from the truth-table for *or*, the table for *and* can be also generated using the **min** operation, in agreement with the definition for set intersection.

In fuzzy reasoning process, one of the major components of fuzzy logic system is *rules*. Rules are expressed as logical implication; i.e. in the forms of IF-THEN statement. On the other hand, rules are a form of proposition. This thus makes the proposition $p \to q$ very important for fuzzy reasoning.

As the same manner for crisp set and fuzzy set, the set of rules containing the IF-THEN statement "IF x is A", THEN y is B" where $x \in X$ and $y \in Y$, has a membership function $\mu_{A\to B}(x, y)$ where $\mu_{A\to B}(x, y) \in [0,1]$ is formed to perform a fuzzy reasoning process. Noted that $\mu_{A\to B}(x, y)$ measures the degree of truth of the implication relation between *x* and *y*. The fuzzy version of equations (5.11) and (5.12) are:

$$\mu_{A\to B}(x, y) = 1 - \min[\mu_A(x), 1 - \mu_B(y)] \tag{5.13}$$

and

$$\mu_{A\to B}(x, y) = \max[1 - \mu_A(x), \mu_B(y)] \tag{5.14}$$

Mamdani Reasoning Method

The rule IF "*Partial discharge is High*" THEN "*Cable condition is Poor*" is called *implication* because the value of *Partial discharge* implies the value of *Cable condition*. Although there are several kinds of fuzzy rule based system such as Larsen's product operation rule or Takasi-Sugeno system, the Mamdani [111] seems to gain widely acceptance in all fields such medicine, economics, engineering etc. This is due to that it can provide a highly intuitive knowledge base that is easy to understand and maintain [112].

If A and B are two fuzzy sets, not necessarily on the same universe, the Mamdani implication is defined

$$A \rightarrow B \equiv A \circ \mathbf{.min}\, B \tag{5.15}$$

Where $\circ$**.min** is the outer product, applying **min** to each element of the cartesian product of A and B.

Let A be represented by a column vector and B by a row vector then their outer min product may be found as multiplication table shown in table 5.6.

Table 5.6 The cartesian product of fuzzy sets A and B using Mamdani implication

$\circ$**.min**	B_1	B_2	…	B_m
A_1	$A_1 \wedge B_1$	$A_1 \wedge B_2$	…	$A_1 \wedge B_m$
A_2	$A_2 \wedge B_1$	$A_2 \wedge B_2$	…	$A_2 \wedge B_m$
…	…	…	…	…
A_n	$A_n \wedge B_1$	$A_n \wedge B_2$	…	$A_n \wedge B_m$

The outer min product of Mamdani is the basis for most fuzzy inference system; therefore it will be used in the work of this thesis.

Fuzzy Inference

In order to draw conclusions from a rule base it needs a mechanism that can produce an output from a collection of IF-THEN rules. This is done using the compositional rule of inference. The verb *to infer* means to conclude from evidence, deduce, or to have as a logical consequence.

A fuzzy model determines the relationships between the inputs and outputs of a system using linguistic antecedent and consequent propositions in a set of IF-THEN rules. The fuzzy model of a multi-input single-output (MISO) system may be formulated in a set of IF-THEN rules as follows: [113]:

$$R_i : \text{IF } x_1 \text{ is } A_{i1} \text{ AND } x_2 \text{ is } A_{i2} \text{ AND } \ldots\ x_j \text{ is } A_{ij} \text{ THEN } y \text{ is } B_i,\ \ i = 1, \ldots, n \tag{5.16}$$

where R_i represents the i^{th} rule, n is the total number of rules, x_j (j = 1,…, r) are the input variables, y is the only output variable, A_{ij} are input fuzzy sets defined in the input space specified by r universes of discourse U = U_1 x …, U_r and B_i is the output fuzzy set defined in the output universe of discourse V. Thus, every rule is a local fuzzy relationship in UxV that maps a part of the multidimensional input space U into a certain part of the output space V.

The rule base of a complex system usually requires a large number of rules to describe the behavior of a system for all possible values of the input variables, referred to as completeness. Hence, the appropriate number of rules depends on the complexity of the system in which the number of fuzzy rules corresponds to the order of a conventional model. The aggregation of the rules of equation (5.16) forms a rule base that is valid over the entire application domain and is given by,

$$R = \bigcup_{i=1}^{n} R_i = R_1 \text{ ALSO } R_2 \text{ ALSO } \ldots R_n \tag{5.17}$$

From equation (5.16) and (5.17) it can be concluded that the fuzzy inference engine consists of three connectives:

1) Aggregation of antecedents in each rule (AND connectives);
2) Aggregation of the rules (ALSO connectives); and
3) An inference based on implication relation (i.e. IF-THEN connectives).

The type of operators performing these three connectives distinguishes fuzzy inference methods. The AND and ALSO connectives are chosen from a family of t-norm and t-conorm operators, respectively. Comprehensive discussions on t-norm (e.g. minimum and product operators) and t-conorm (e.g. maximum and sum operators) can be found in [145, 146, 147]. The IF-THEN connectives also use t-norm operators, not necessarily identical to the ones used for the AND connectives. An efficient method of reasoning involves first inferring from individual rules, and then aggregating the results, called first-infer-then-aggregate (FITA). And among all FITA fuzzy reasoning methods, Mamdani's approximation reasoning is most common in fuzzy logic control and modeling applications.

5.2.2 Fuzzy Inference System (FIS)

FIS Architecture

A connection between cause and effect, or condition and a consequence is made by reasoning. Reasoning can be expressed by a logical inference or by the evaluation of inputs in order to draw a conclusion. A fuzzy inference process, one kind of logical inferences, maps the crisp inputs into the crisp outputs. The flow of the process is depicted in figure 5.4.

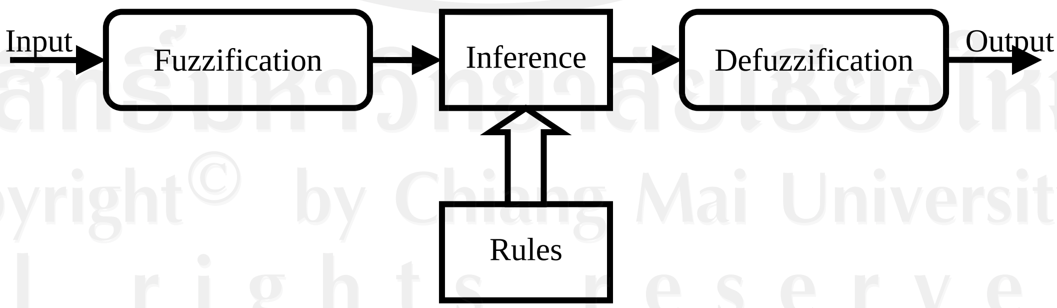


Figure 5.4The fuzzy inference system (FLS).

There are four key components that form the FLS: knowledge base (rules), fuzzification, decision making logic (inference), and defuzzication.

Rules which contained in knowledge base may be provided by experts or can be extracted from numerical data. In either case, the knowledge rules are expressed as a collection of IF-THEN statement, an implication operation of logical proposition. From example above, the rule: IF "*Partial discharge is High*" THEN "*Cable condition is Poor*" reveals the needs to understand [106]:

1) Linguistic variables versus numerical values of variables;
2) Partitioning linguistic variables into fuzzy sets using membership function;
3) Logical connections for linguistic variables, e.g. "and", "or", etc.;
4) Implication, i.e. "IF A THEN B".

Apart from its intuitive handling and simplicity, the success of fuzzy inference process is mainly due to its closeness to human perception and reasoning [112]. Human experts are thus the main knowledge source for establishing the knowledge rules. Expert knowledge are utilized to from the IF-THEN rules which are then stored in the knowledge base. Another source of knowledge is embedded in the data itself. The relation between input and output numerical data can be used to form the knowledge rules [114]. In conclusion, there are basically four approaches to the derivation of fuzzy knowledge rules [115]:

1) From expert experience and knowledge,
2) From behavior of human operators,
3) From the fuzzy model of a process, and
4) From learning.

Table 5.7 The example of fuzzy knowledge rules.

Rule#	**Cable Age**	**Load Current**	**Ambient Temp**	**Failure Possibility**
1	moderate	low	low	low
2	old	high	high	high
3	moderate	medium	medium	low
4	young	high	high	high
5	young	medium	high	medium
…	…	…	…	…
N				unknown

Table 5.7 above shows the samples of knowledge rules used for determining the possibility of cable failure when operating under various condition. Rule#2 can be read as IF the age of cable is old and electric current flown in cable is high and the ambient temperature is high THEN the possibility of cable failure is very high.

Fuzzification is the process of decomposing a system input and output into one or more fuzzy sets. On the other hand, the fuzzification process maps crisp numbers into fuzzy sets. Fuzzification of a real-valued variable is done with intuition, experience and analysis of the set of rules and conditions associated with the input data variables. There is no fix set of procedures for the fuzzification. There are many types of membership functions or curves, as described in previous section, are used for fuzzification. The most common used in decision making process would be singleton, Gaussian and trapezoidal or triangular fuzzifier [116]. Figure 5.5 shows fuzzy sets of a system input with trapezoidal and triangular membership functions. Each fuzzy set spans a region of input (or output) value graphed with the membership. Any particular input is interpreted from this fuzzy set and a degree of membership is interpreted. The membership functions should overlap to allow smooth mapping of the system.

The process of fuzzification allows the inputs and outputs to be expressed in linguistic terms so that rules can be applied in a simple manner to express a complex system. Fuzzification is needed in order to activate rules which are in terms of linguistic variables, which have fuzzy sets associated with them.

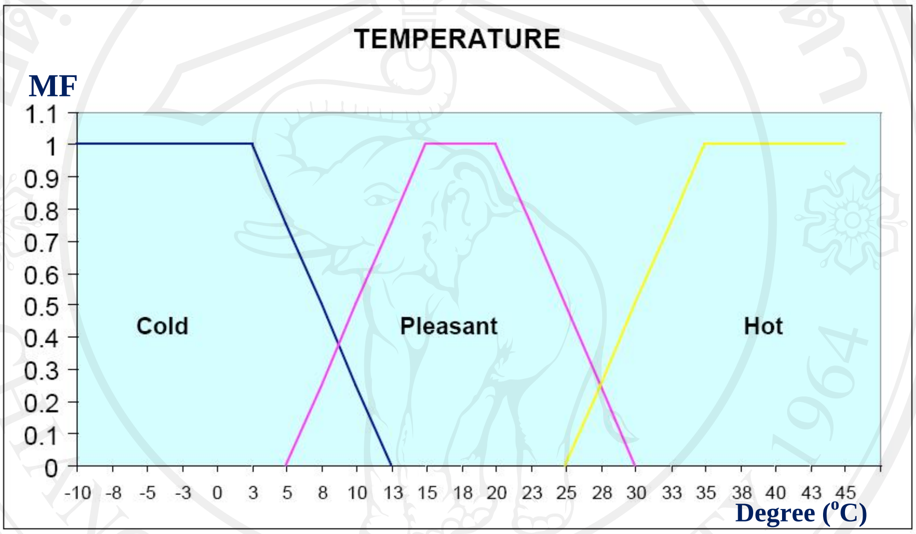


Figure 5.5 Fuzzy sets defining temperature

It should be remarked that the fuzzification of input variables should be realistic. Experiences and different procedures should be followed while designing a large fuzzy system for the realistic and accurate output. The wrong fuzzification of the input variables might cause instability and error in the system.

Inference engine maps input fuzzy sets into output fuzzy sets. It handles the way in which rules are combined. Just as human use many different types of inferential procedures to help them understand things or to make decision. For example, to draw the conclusion of the cable condition, several input fuzzy sets and several rules are aggregated and evaluated to reveal the output fuzzy set.

Defuzzification process maps output fuzzy sets into a crisp number. After fuzzy reasoning a linguistic output variable is needed to be translated into a crisp value. The objective is to derive a single crisp numeric value that best represent the inferred fuzzy values of the linguistic output variable. For example, in evaluating the possibility of cable failure, one might want to know the numerical percentage of failure possibility. Defuzzification is such inverse transformation which maps the output from fuzzy domain back into the crisp domain. The following defuzzification methods are of the most practical use [116,117].

Maximum Defuzzification Technique: This method gives the output with the peak of the membership function. This defuzzification technique is very fast but is only accurate for peaked output. This technique is given by algebraic expression as:

$$\mu_A(x^*) \geq \mu_A(x) \text{ for all } x \in X \tag{5.18}$$

Centroid Defuzzification Technique: This method is also known as the center of gravity center of area method because it computes the centroid of the composite area representing the output fuzzy term. This is the most commonly used technique and is very accurate. This technique can be expressed as:

$$x^* = \frac{\int \mu_i(x)xdx}{\int \mu_i(x)dx} \tag{5.19}$$

where x^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable. The only disadvantage of this method is, however, that it is computationally difficult for complex membership functions.

Weighted Average Defuzzification Technique: In this method the output is obtained by the weighted average of each output of the set of rules stored in the knowledge base of the system. The weighted average defuzzification technique can be expressed as:

$$x^* = \frac{\sum_{i=1}^{n} m_i w_i}{\sum_{i=1}^{n} m_i} \tag{5.20}$$

where x^* is the defuzzified output, m_i is the membership of the output of each rule, and w_i is the weight associated with each rule. This method is computationally faster and easier and gives fairly accurate result.

Applications of Fuzzy Inference System

Fuzzy system has 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). Fuzzy system has also extended its usage to other application area such as medical, law, biological, or environmental application. Fuzzy logic can reduce the source of error in a business process modeling which regularly encounters an unclear and ambiguous situation and unreliable data. Fuzzy set can depict the uncertainty on the cost driver; thus cost driver uncertainties have less impact on the business model [118]. In power system domain, fuzzy set theory methodology is employed for handling and overcoming various forms of uncertainty in all phases of implementation activity. The paper [119] shows that fuzzy set theory can be applied in the planning related area, operation area, control area and diagnosis. The claim was later strengthened by the paper [120] that the area of power system control, power system decision making and optimization, and diagnosis of power system condition. It is applied for determining the depreciation of power equipment, derived from measured data using fuzzy logic rules set by experts [121, 122].

The applications fuzzy logic technology within power systems are extensive with hundreds archival publications in a recent survey. Several of these applications have found their way into practice and fuzzy logic methods are becoming another important approach for practicing engineers to consider [104]. Table 5.8 illustrates the application of Fuzzy set in power system domain.

Table 5.8 Fuzzy set application areas in power systems [123].

- 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

The application of fuzzy inference system in dealing with risk in power distribution system will be however thoroughly investigated in the latter sections of this chapter.

5.3 Markov Chain

Most of study of probability has dealt with independent trials processes. These processes are the basis of classical probability theory and much of statistics. It can be seen that when a sequence of chance experiments forms an independent trials process, the possible outcomes for each experiment are the same and occur with the same probability. Further, knowledge of the outcomes of the previous experiments does not influence predictions for the outcomes of the next experiment. The distribution for the outcomes of a single experiment is sufficient to construct a tree and a tree measure for a sequence of *n* experiments, and it can answer any probability question about these experiments by using this tree measure. Modern probability theory studies chance processes for which the knowledge of previous outcomes influences predictions for future experiments. In 1907, A. A. Markov began the study of an important new type of chance process. In this process, the outcome of a given experiment can affect the outcome of the next experiment. This type of process is called a *Markov chain* [124].

In condition based deterioration modeling the attributes of a model randomly change over time. A Markov chain is a probability model, which has a finite-state (countable state), for describing a certain type of stochastic process that moves in a sequence of phases through discrete points in time according to fixed probabilities. The process is stochastic because it changes over time in an uncertain manner. In this chain the future states are dependent only on the present state and independent from the any state before the present states. Markov chain consists of transition matrix and initial distribution. Time can be treated as either discrete (called discrete-time Markov chain) or continuous (called continuous-time Markov chain). In Markov chain the states are continuous and similarly the time could be either discrete (called discrete-time Markov process) or continuous (called continuous-time Markov process).

Although the deterioration processes evolve over continuous time, for simplicity discrete time steps could represent these processes (such as the time of the equipment inspection). Hence in this thesis the discrete time Markov chain will be considered as a model for predicting the life cycle for building element.

5.3.1 Transition Probability

Discrete time Markov chain is a finite-state stochastic process in which the defining random variables are observed at discrete points in time. This chain satisfies Markov property which means that given that the present state is known, the future probabilistic behavior of the process depends only on the present state regardless of the past.

Let $S = \{s_1, s_2, \ldots s_r)$ is a set of states. The process of Markov chain starts in one of these states and moves successively from one state to another. Each move is called a step. If the chain is currently in state s_i, then it moves to state s_j at the next step with a probability denoted by p_{ij}, and this probability does not depend upon which states the chain was in before the current state. The probabilities p_{ij} are called *transition probabilities*. The process can remain in the state it is in, and this occurs with probability p_{ii}. An initial probability distribution specifies the starting state. Usually this is done by specifying a particular state as the starting state. A nice description of a Markov chain is given by R. A. Howard as a frog jumping on a set of lily pads. The frog starts on one of the pads and then jumps from lily pad to lily pad with the appropriate transition probabilities.

In order to gain a full insight of how Markov chain work, let assume a set of state of a certain object be $S = \{1, 2, 3\}$. The example of this could be a set of possible weather condition in a given day; e.g. S = {Sunny, Rainy, Snowy}. The probability for the condition state transitioning into the next state can be formed as:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix}$$

In row 1 of matrix **P**, It can be interpreted as if the weather is now in state 1, i.e. sunny state, the probabilities that the condition of this object would transition into the later state are:

- p_{12} for transitioning from sunny to rainy state;
- p_{13} for transitioning from rainy to snowy; and
- p_{11} for remaining in sunny state.

The above example can be illustrated by pictorial description as shown in figure 5.6.

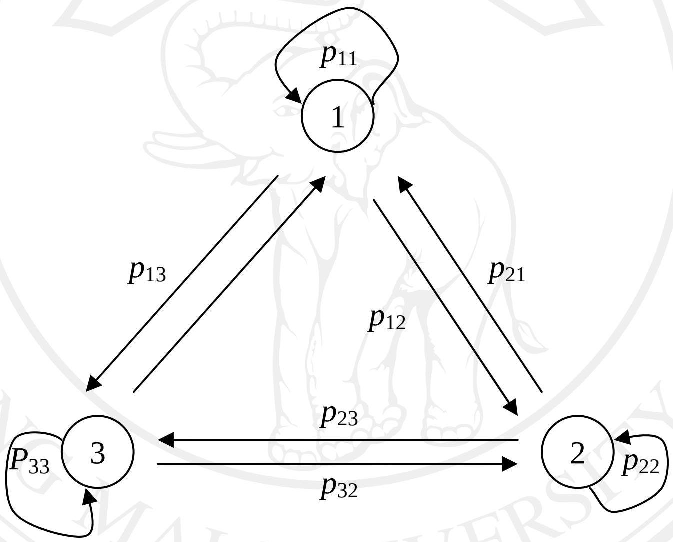


Figure 5.6 Transition of states

In general form, the matrix of state transition can be denoted as:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \cdot & p_{1i} & p_{1j} & \cdot & p_{1r} \\ p_{21} & p_{22} & \cdot & p_{2i} & p_{2j} & \cdot & p_{2r} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{i1} & p_{i2} & \cdot & p_{ii} & p_{ij} & \cdot & p_{ir} \\ p_{j1} & p_{j2} & \cdot & p_{ji} & p_{jj} & \cdot & p_{jr} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{r1} & p_{r2} & \cdot & p_{ri} & p_{rj} & \cdot & p_{rr} \end{bmatrix} \qquad (5.21)$$

where state 1 is an initial state and state r is a final state. The matrix **P** whose ij^{th} entry is p_{ij} is called the *transition matrix*. In Markov chain p_{ij} should satisfy two conditions:

$$\sum_{i=1}^{r} p_{ij} \leq 1 \text{ and } p_{ij} \geq 0 \tag{5.22}$$

This means if an object is in state i, there is a probability (p_{ii}) that this object will stay in state i, and (1-p_{ii}) will change to another state.

Now let consider the question of determining the probability that, given the chain is in state i presently (or $X_t = i$); it will be in state j in the next time step (or $X_{t+1} = j$). The Markov property is defined as:

$$P(X_{t=1} = j \middle| X_t = i, X_{t-1} = i_{t-1}, \ldots, X_0 = i_0) = P(X_{t=1} = j \middle| X_t = i) \tag{5.23}$$

From weather condition example, if the time step t is the number of days, it is obvious that the probability of raining tomorrow (t + 1) given that today is sunny day is p_{ij}; what it would be for two days from now? It can be seen that if it is sunny today then the event that it is rainy two days from now is the disjoint union of the following three events:

1) it is sunny tomorrow and rainy two days from now,
2) it is rainy tomorrow and rainy two days from now, and
3) it is snowy tomorrow and rainy two days from now.

The probability of the first of these events is the product of the conditional probability that it is sunny tomorrow, given that it is sunny today, and the conditional probability that it is rainy two days from now, given that it is sunny tomorrow. Using the transition matrix **P**, we can write this product as $p_{11}p_{12}$. The other two events also have probabilities that can be written as products of entries of **P**. Thus, we have

$$p_{12}^{(2)} = p_{11}p_{12} + p_{12}p_{22} + p_{13}p_{32} \tag{5.24}$$

This equation is a dot product of two vectors by dotting the first row of **P** with the second column of **P**. This is just what is done in obtaining the 1; 3-entry of the product of **P** with itself. In general, if a Markov chain has r states, then

$$p_{ij}^{(2)} = \sum_{k=1}^{r} p_{ik} p_{kj} \tag{5.25}$$

If **v** be the probability vector which represents the starting distribution. Then the probability that the chain is in state i after t steps is the i^{th} entry in the vector

$$\mathbf{v}^{(t)} = \mathbf{v}\mathbf{P}^{t} \tag{5.26}$$

The ij^{th} entry $p_{ij}^{(t)}$ of the matrix $\mathbf{P}_t$ gives the probability that the Markov chain, starting in state i, will be in state j after t steps.

5.3.2 Probability of Absorption

An absorbing state is a state of which there is a *zero probability of exiting*. An absorbing state is a state j with $p_{jj} = 1$. A Markov chain is absorbing if it has at least one absorbing state, and if from every state it is possible to go to an absorbing state (not necessarily in one step). In an absorbing Markov chain, a state which is not absorbing is called *transient*. Example of absorbing is, without any maintenance action, the equipment which reached *failed* condition will stay in that condition forever. Calculating the expected number of steps to absorption (equipment pass from different states to end up in failed state) can help to obtain an overall view about the estimated life cycle for that equipment.

To calculate the absorbing states, let 0, 1,…, k be transient states and $k + 1$, …, $m - 1$ be absorbing states. Let q_{ij} = probability of being absorbed in state j given that we start in transient state i. Then for each j we have the following relationship

$$q_{ij} = p_{ij} + \sum p_{ir} q_{rj}\ ,\ \ i = 0, 1, \ldots, k \tag{5.27}$$

For fixed j (absorbing state) we have $k + 1$ linear equations in $k + 1$ unknowns, q_{ij}, i = 0, 1,…, k.

5.3.3 Markov Process in Asset Condition Assessment

To apply the Markov process in assessing the condition state of a certain infrastructure asset, two important information needed to be formulated in order reach a conclusion what state an asset is in at any given time point; that are an initial condition state and a deterioration rate. But first the life of an asset has to be discretized into time steps and the Markov process is applied at each time step in two stages. In the first stage, the deterioration rate at the specific time step is inferred from the asset age and condition state using a particular algorithm. In the next stage, the condition state of the asset in the next time step is calculated from present condition state and deterioration rate. Essentially the deterioration process models the asset as it gradually undergoes change from better to worse condition states. This deterioration model yields the possibility of failure at every time step along the life of the asset. A first step to use the deterioration model is to train (calibrate) it on condition rating of a specific asset (e.g. distribution feeder), obtained from one or more inspections. Once the deterioration model has been trained, it can be used to predict the future condition of such asset.

Let pick an example to describe in detail to gain a full insight of how a certain asset deteriorates itself and how a deterioration rate in a form of transition matrix can be formulated. Suppose that an asset has three condition grade (or state): *good*, *poor*, and *failed*. The deterioration matrix can be formed as:

$$\mathbf{D} = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} \tag{5.28}$$

For the sake of practicality, however, two assumptions have been made. First, it is reasonably assumed that an asset cannot improve itself without any intervention, e.g. maintenance action. Second, it is assumed that the deterioration process is continuous and slow relatively to the selected time step, therefore, an asset in state *i* can at the most deteriorate to state *i*+1 within a single time step. In addition, if the probability of state change is d_{ij} it means that the probability of remaining in the same state is 1- d_{ij}. Equation (12) thus can be rewritten as:

$$\mathbf{D} = \begin{bmatrix} 1-d_{12} & d_{12} & 0 \\ 0 & 1-d_{23} & d_{23} \\ 0 & 0 & d_{33} \end{bmatrix} \qquad (5.29)$$

Now let assume the condition grade of asset starts at a good condition (*i*=1) and the probability that asset deteriorate itself from initial to next state is, say, 10%, it can be said that asset loses 10% membership to state *i* in favor of state *j* (*j* = *i* + 1) as it transits from time step *t* to *t* + 1. The membership of asset belonging to each condition state at different time points can be graphically illustrated in figure 5.7. Using the information obtained from figure 5.7, it is possible to predict the condition of a considered asset at any point in time, given a present condition state.

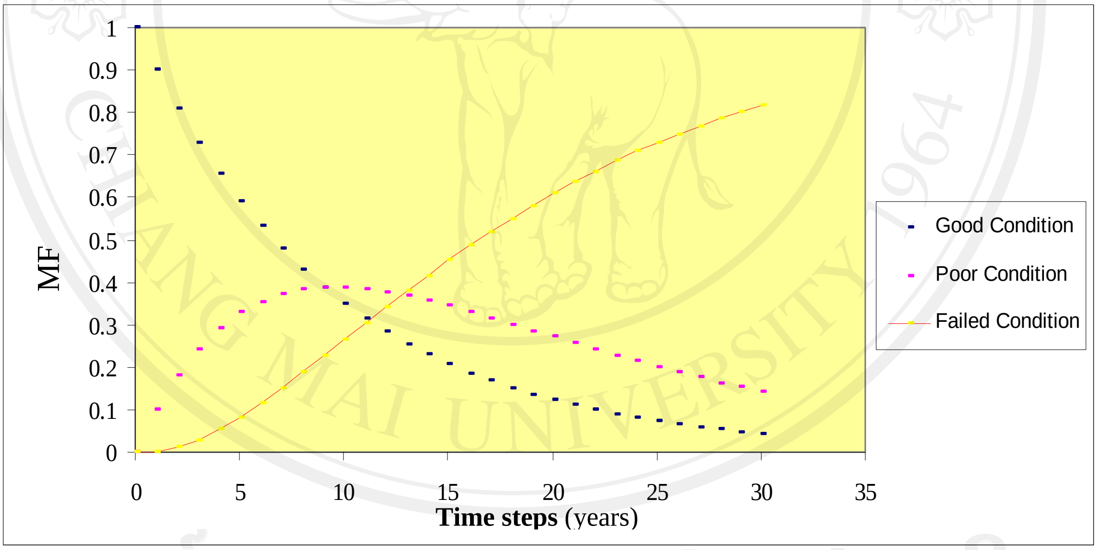


Figure 5.7 Membership of condition state at different time steps

The question now is how 10% deterioration from the better to the worse of previous example is obtained and what condition state is the asset currently in? These two questions are the fundamental knowledge for asset condition assessment. However, the answer to these two questions as well as the use of Markov chain for assessing the asset condition will be discussed in the later section.

5.4 Fuzzy-Markov Assessment of Distribution Network Failure Possibility

The distribution network connects the end users to the electric power. The failures of distribution network cause the power outage to customers which in turns results in various consequences, both economical and non-economical. The problem that utility asset managers come across is they do not know for sure *if* or *when* a failure would occur.

In order to assist the asset managers successfully perform the reinforcement planning of the network infrastructure, two main questions need to be systematically resolved: *what is the condition of the network asset and what is the possibility of its failure*? The first question can be resolved by performing the performance testing directly on the asset or by knowledge engineering approaches whereas the second obtained by manipulating the results from the first question with operational and environmental stresses.

This section first addresses the causes that make the distribution network components that compose the distribution feeder such as cables, wires, or insulators to deteriorate which in turns leads to the feeder failure. Then the condition grade of feeder components will be examined and manipulated in order to obtain the overall feeder's condition rating. Finally, the possibility of feeder failure could be determined by taking into account both feeder's condition rating and its operational stresses and external environment.

5.4.1 Distribution Feeder Component Deterioration and Failure

Factors that determine the long term behavior and performance of utility infrastructures include their intrinsic properties, their operating conditions as well as their external environment [125]. Examples of asset intrinsic property may be material, serviced age and design while its operating condition includes current and voltage presence on the circuit and the external environment might be temperature, weather condition, and contact of trees or accidents. Power distribution system infrastructure, particularly the distribution feeder is composed of various electrical power components and operated under various conditions and environments; the performance of power distribution system as a whole is thus dependent on the performance of individual components of which also governed by its design and environment of use.

The distribution feeder is designed and built in such a way that carries an electric current without excessive heat and withstands electric potential with no breakdown. This current is regarded as a nominal and dynamic current whereas the voltage withstand capability is called basic insulation level (BIL). Once these two components are violated, the feeder may fail to perform its function. However, although the magnitude of above mentioned parameters is still within the designed range, if the component condition deteriorates or the operating environment goes beyond the preset value, the feeder may also fail. Another factor that can impact the performance of feeder is the mechanical forces placed on the feeder components.

Reference [126, 127, 128] has addressed the events and phenomena that make distribution network fail which include:

- Trees
- Animals
- Vehicular accidents
- Construction accidents
- Overload
- Short-circuit, ground fault

- Poor wiring or bus connection
- Weather condition (hot, humid)
- Natural phenomena (ice, wind, lightning, storm, earthquake)
- Damage (mechanical)
- Personnel
- Materials, designs
- Pollution
- Others

When analyzing the events listed above, it is uncovered that the failure modes of distribution feeder fall into three categories. They include thermal, electrical and mechanical strike. The description of each is given as follows.

Thermal Failure

As mentioned previously, the feeder is design in such a way that can carry load current without excessive heat occurred on the feeder wire. But due to the resistance (R) of electrical wire, if there is an electric current (I) flowing in the wire there will be heat produced in terms of I^2R. If this heat is not dissipated away appropriately, the wire will deteriorate its mechanical strength and burn up its insulation. Factors that aid or hinder the heat dissipation are refill (surrounding substance), temperature and air ventilation. Under normal circumstances, the heat produced in wires is able to dissipate away sufficiently. When the feeder is overloaded, the heat produced will outnumber the ability to dissipate. This will gradually damage feeder conductor and its insulation. In short-circuit circumstance; a vast amount of heat produced by short-circuit current can sometimes burn up the wire especially in the portions that have higher resistance such as joint or connection. The short-circuit events occur when there is a low resistance connection from between phase conductors or from phase conductors to earth. The situations that lead to short-circuit include tree contacts, accidents, weather or natural phenomena.

Electrical Failure

An overvoltage occurs when an electrical device or circuit experiences a voltage value of much greater than the value it is designed to operate. Under normal voltage level, the insulation strength of an electrical device is sufficient to withstand an electrical stress produced from such voltage. However, when voltage becomes very much higher, this stress locally damages parts of insulation material and eventually breaks down the entire insulation. There are two type of overvoltage imposed on the distribution feeder. One is from lightning strike; another is from ground fault on ungrounded neutral system. The breakdown that caused by overvoltage results in short-circuit events on distribution feeder.

Mechanical Failure

Mechanical failure may be caused by an act of mechanical forces strike or hit directly on the network components. It results in short-circuit, deformation or breakage of the components which in turn causes the components not able to function properly or even breakdown. The examples of mechanical contact can range from harsh events such as vehicular and constructional accidents, storms, earthquakes, etc. which make the component deform or breakdown to soft events such tree contact, living creature or human touching which cause high resistant fault. The severe attack results to mechanical failure mode.

Short-circuit incident itself also creates a mechanical shock on the feeder components. Electromechanical forces produced by a large amount of short-circuit current try to move the conductor away from its position. Components breakage or movement away from its correct position can be expected.

Another mechanical failure may be originated from chemical deterioration on network components. When the mechanical strength of components deteriorates to the degree where they cannot withstand its mechanical load, these components will eventually breakdown. The rust occurs on steel components is an example of this type.

5.4.2 Determination of Distribution Feeder Asset Conditions

The asset condition is one of contributing factors that cause the distribution feeder to fail. To deal with asset condition evaluation, the deteriorating behavior of distribution asset needed to be first reviewed in order to gain a better understanding of deterioration mechanism. Although the deterioration may not lead to the sudden breakdown of electrical components as described in the failure mode mechanism, it is in fact shortening component’s life. Deterioration is a gradual process. When it reaches the state where electrical components can not tolerate the heat or voltage stress, the electrical components will eventually break down. The usual causes for distribution network component deterioration are more or less the same as those that make components fail where some major sources are discussed as the followings.

- *Short-circuit*: The maximum current carrying capacity of a power cable under steady state conditions is determined by equating the heat generated within the cable and the heat which can be designated to the cable surrounds [129]. Apart from being able to carry the normal design load of a circuit a cable has to be capable of carrying the potential fault current of a system without significantly shortening the expected service life of the cable because under short-circuit circumstance, a large amount of short circuit current suddenly heat up the conductor if not being dissipated away quickly and sufficiently, it may burn up the conductor and insulation materials. Furthermore, the mechanical force produced by the high amount of short circuit current may try to displace the component from its original position which in turn put this component under sustained stress, make it deform or even worse damage the component.
- *Lightning strike*: Extremely high voltage from lightning may cause the insulation of wire to deteriorate [130]. Under high voltage stress, the weak spot inside insulation material of wire and cable may locally break down; cause the overall insulation strength weakening. This weakening mechanism if occurs is somehow difficult to observed.

- *Natural deterioration*: As its name implies, is the ageing process that can occur in every physical object. As the time goes by, the life of the asset is being gradually shortened.
- *Thermal ageing*: The results of temperature variation in electrical components due to the heat cycle during network operation.
- *Partial discharge (PD)*: PD mechanism occurs in solid electrical insulation such as porcelain insulators, ceramic insulators, or polymeric insulator. PD is a localized dielectric breakdown of a small portion of a solid electrical insulation system under high voltage stress. It usually begins within voids, cracks, or inclusions within a solid dielectric. When PD spreads out to the state where insulation cannot withstand the applied voltage, it causes the equipment breakdown.
- *Pollution*: although by itself is not the deterioration but it originates and help escalates the process of deterioration. For example, the salt deposited on the insulator surface may cause the surface tracking and develop the PD, or water that seeped into polymeric insulation of cable causes the phenomena called water tree which later developed into electrical tree (or PD) when put under voltage stress. The steel components may suffer the rust problem if placed in hot and humid environment.

The condition assessment of power distribution network assets is a time consuming and costly procedure. It may be classified into two categories. The first involves the measurement and testing, either offline or online, directly on the assets; this is viewed as an objective method [131]. The power cables for example, tan delta and partial discharge test could be performed to detect the developing water tree and any other defects in XLPE insulated cable [132]. The second process might be regarded as a subjective method which requires a judgment from domain experts against the obtained data especially those obtained from visual inspection [131]. It may be made in two alternative ways; this includes:

1) Expert simply indicating the condition grade of considered asset after fully studying involved data and

2) Forming a set of knowledge rules and allowing machine to manipulate data and bring about a condition grade.

In the second option, the distress indicators indicating the degradation of assets are aggregated and translated into an overall asset condition grade. Distress indicator in this context is signs, traces or adverse experiences stressed on the assets which can be measured, observed, or approximated in some quantifiable forms.

It is important to note here that environmental or operational stresses or mechanisms that lead to network asset deterioration (ageing) are not explicitly considered to determine its condition rating [133]. It is suggested that the observable or measurable distress indicators are a testament to the combined impact of all the stresses (operational, environmental) that ever acted on the feeder. In other words, any adverse impact on the feeder components such as arcing, cracking, hot spots, etc. will manifest itself in some form of observable distress and would be detected in the inspection.

Since power distribution circuits are composed of numerous parts, all of which can fail in one or more ways, routine inspections programs can be used to identify problems for taking countermeasure action before they develop into failures. Utilities conduct the inspection programs to enhance the quality and reliability of electric service [134]. In distribution feeder asset condition assessment, the distress indicators can be obtained in two ways: visual inspection and measurement.

Visual inspection is regarded as the most cost-effective method in condition assessment. It can be applied to many kinds of equipment especially the overhead facility where all the components are made visible to eye contact. Many deficiencies can be found through a simple visible examination. Visual inspection can, however, be simply made by naked eyes contact or using the telescope or binocular to enhance visualization. Broken or damaged equipment, severely aged equipment, and improperly built structures can be visually identified [135]. Basic visual inspections are widely applied to evaluate circuit conditions and look for any deficiencies or problems that could lead to faults. However, if such deficiency can be simply corrected with less effort, less price and within short period of time, although it is a sign of degradation it is not, for condition assessment case, regarded as distress indicator. Whether or not the deficiency found is considered as the distress indicator is dependent on expertise guideline and judgment.

In case that the condition of the components where visual contact is not possible or when condition rating judgment cannot be simply made upon the visual contact, the measurement and test may be required for this case. Deterioration by water tree or partial discharge activities in underground cable insulation is example of this kind. This type of deterioration can be detected by measuring the dissipation factor and partial discharge that have been developed on such component. It is however needed the historical database and expertise judgment

Since the distribution network components are diverse, the results from inspection and measurement are also varied; the level of feeder degradation may not be precisely identified. The hierarchical breakdown structure of feeder components is formulated to derive the overall condition of the feeder. For example, the feeder components may be grouped into pole structure, conductor assembly, lightning protection, or circuit switches for an overhead distribution feeder; and the groups of cable container, cable component and switches for an underground feeder. The details of such categories were discussed in chapter 4 and are summarized as shown in Appendix A1. Each distress indicator would provide evidence (hint or contribution) to the condition of the specific component while component provides partial contribution to the expected condition rating of the category. In turn, each category partially contributes to support the overall rating of asset. The contribution of each distress indicator towards a specific component, as well as the contribution of each component and category towards the final condition rating, is assessed from well-documented case inspection and measurement results as well as from known behavior and performance of feeder components, engineering judgment and expert knowledge.

Another question that needs to be answered is how the distress indicator, condition rating of specific component as well as the degree of contribution can be actually obtained. This can be achieved through the process of knowledge engineering. The process includes setting a guideline for formulating distress indicator, establishing assessment criteria and forming an assessment form.

References [134, 135] has provided a very useful guideline on what to look for in order to find the deficiency existed on the network components which in turn employed as distress indicator for condition assessment. The followings paragraphs provide explanation of such guideline.

Inspection of Overhead Distribution Line

Pole

Examine the pole from the groundline up for signs of rot, decay, infestation, splits, breaks, or burns. Cracking and separation on surface of concrete pole shall be reported. Pay particular attention to the pole top as that area has the greatest lightning exposure and tends to hold most of the equipment. Excessively leaning poles should also be noted.

Crossarms and Braces

Verify the integrity of all crossarms if there exist any signs of rusty, broken, split, cracked, twisted, rotating, detached, or otherwise deteriorated. Also look for burn marks. Examine all crossarm bracing for bends, splits, breaks, detachment, etc.

Guys Lines

Examine any pole guy attachments and guy wires. Do all appear to be in good shape? Do any of the guy lines appear worn, frayed, or broken? Check that the guy lines are not slack or bent around any objects. Check that all guy lines have adequate clearance to energized equipment and conductors. Also verify that guy guards are in use when appropriate. Finally, check the anchor rods for damage or decay. Does the anchor rod appear to be bending or pulling? Is the anchor rod eye above ground level?

Conductors

Look for inadequate conductor clearances with buildings, roadways, other wires, etc. Check for excessive phase sag which is out of specification, violates clearance standards, or could resulting increased conductor slapping activity during windy conditions. Do any portions of the conductor appear frayed, broken, or burned?

Insulator

Look for broken, cracked, or chipped ceramic insulators. For polymer insulators, look for tears, punctures, and broken rods. For all insulators, do they appear excessive contaminated, flashed, or burned? Check for grossly misaligned insulators and uplifting or floating on non-dead end insulators. Are appropriate wire ties used? Is the conductor insulation stripped back when appropriate to prevent conductor burn-down?

Arresters

Verify that arresters appear to be in good working order. Does the arrester body have any tears, punctures, chips, or cracks? Sometime arresters even break completely apart. Look for defects that could allow water to penetrate into the arrester. Are there any signs of flashing on the arrester body? Look for excessive lead lengths. As previously mentioned, it is vital for arrester installations to have the shortest lead length possible. Also check arrester clearances and make sure that if the isolator operates that the lead won't swing into other energized conductors. Verify proper wildlife guard installation where required by company specifications.

Ground Wire

Examine pole grounds for cuts, breaks, abrasions, or other damage. Does the ground wire appear to be adequately supported on the pole? Verify that ground guards are in place. Is there adequate clearance between the ground wire and energized conductors, especially near the pole top?

Fuses and Cutouts

Do the cutout brackets appear to be in good working order? Are there any signs of flashing, damage, or sever weathering? Look to make sure that the brackets are plumb and do not appear to be pulling away from the crossarm.

Transformers

Examine transformers for rust or damage. Leaking transformers should be immediately reported for containment, clean-up, and replacement. Look for signs of overheating, or flashing, especially around the bushings. If required, are wildlife guards in place and properly installed? Do the transformer leads have adequate clearances? Verify that the transformer's arresters and fuses appear to be in good working order as well.

Other Equipment

Line equipment such as capacitors banks, reclosers, and regulators should be examined for signs of rusting, leaking, damage or flashing. Verify that arresters and fuses are properly applied and appear to be in good working order.

Inspection of Underground Distribution Line

Above Ground

Make sure the cover is in good physical condition and fits the opening properly. If a vented cover is used to verify that the vents are clear of debris. Also check to see that the cover is at grade.

Water and Debris

Look for water and debris in the structure. Does the structure need to be pumped or cleared before inspection? Are the cables or equipment submerged? Are the ducts freed of debris? Verify proper operation if a sump pump is present (this can usually be accomplish by lifting the float switch and observing the pump starting).

Structure Conditions

Check the overall cleanliness and physical condition. Look for cracks, spalling or exposed rebar. Check the condition of the floor and roof in addition to the walls. If cover tethers are used verify that they are installed properly and appear to be in good physical condition.

Racks and Saddles

Do the cable racks, saddles, and other structural components appear to be in good working order? Are any saddles missing their porcelain inserts?

Ducts

Are the duct entrances chipped or cracked and in need of grouting? Are the ducts properly sealed?

Cables, Services, and Other Conductors

Inspect all cables for insulation wear or abrasion. Be especially mindful of exposed conductors and visible burnouts. Is the insulation swollen, damaged, peeling, cracked, or burnt? Do the cables show signs of excessive heating? Inspect for leaking cables.

Joints

Look for leaking, swollen, imploded, or otherwise deformed joints. Do any joints show signs of excessive heating? What about burning or arcing?

Neutral Cable and Connections

Do the neutral conductors and connections appear to be in good working order? Are any bonds broken? Does the neutral bus appear to be in good working order?

Transformers and Other Equipment

Does all equipment appear to be in good working order? Are there any leaks? Are there any cracked or damaged bushings? Does any equipment show signs of arcing, burning, or excessive heating?

Once the distress indicators have been obtained, the knowledge rules can be formed to establish a set of criteria for condition assessment. Domain experts are involved in this course of action. Since individual network component deteriorates in different way, the criteria also differ from one another. The followings provide details on how to lay down criteria for assessment and how the final condition rating of the asset can be achieved. The full set of asset condition assessment forms utilized in this thesis is published in appendix A2.

Based upon the framework of building an FIS Expert System, the Fuzzy synthetic evaluation (FSE) framework has been established to deduce the condition grade of electric distribution feeder from the obtained information of what deficiency that the individual asset (component) has undergone. The knowledge engineering methodology (CommonKADS Classification and Assessment and Ontology101) as discussed in chapter 3 is employed to perform a knowledge acquisition and modeling from domain experts. The evaluation process involves three steps: (1) fuzzification of raw data (quantification or measurements of the distress indicators) and assignment of individual asset condition rating; (2) translation of those condition ratings into overall feeder condition rating by manipulation of condition ratings towards their respective categories, manipulation of categories towards the overall condition rating of feeder; and (3) defuzzification that adjusts the condition rating to a practical crisp format.

(1) Fuzzification of raw data and assignment of individual asset condition rating

Since the distress indicator represents the deficiency found on the inspected component, linguistic values indicating the condition rating (or condition grade which used interchangeably in this thesis) of such asset can be used to form the fuzzy sets of each distress indicator. But how to place a certain level of deficiency into individual fuzzy set may need assistance from domain experts. This task is done with intuition, experience and judgment of utility experts on how significant each distress indicator contributes to the asset degradation process. Based on the work done in many literatures [99, 136, 137, 138], the asset condition rating used in this research is partitioned into 5 so-called rating. The numeric representation of condition rating and corresponding verbal grade and description are shown in table 5.9 below.

Table 5.9 Technical condition states of distribution assets

Grade	**Description**	**Verbal Grade**
1	No noticeable deterioration. Some aging may be visible	good
2	Some deterioration is evident, but the function of component is not significantly affected.	Adequate
3	Moderate deterioration. Ability to function is adequate.	Fair
4	Serious deterioration. Ability to function is significantly affected.	Poor
5	Severe deterioration. General failure or a complete failure of component	Failed

It should be noted that the failed (grade 5) condition state does not mean that breakage or collapse has already happened (in which case the membership would be a definite unity), rather that the asset is in such a bad condition that failure is imminent and can occur at any time as a result of the slightest perturbation.

However, the concept of fuzzy set is applied for condition grading instead of deterministically grading asset condition with those respect crisp value. This would be more realistic because most of the time it is quite difficult to justify what condition state the asset would belong upon the certain inspection. For example, how it should be defined whether the insulator with sign of surface tracking would belong to *fair* or *poor* condition. With the concept of fuzzy set, the fuzzy rating of the previous example could be represented as $(\frac{0}{good},\frac{0}{adequate},\frac{.75}{fair},\frac{.25}{poor},\frac{0}{failed})$ which implies that this insulator belongs to *fair* condition with the degree of 75% and to *poor* condition with the degree of 25%.

As stated before, there are various component types forming the network. Furthermore, there are also a number of components that belong to each component type especially in the overhead distribution network. The question may arise how the component's condition should be represented. In this thesis, the concept of "worst represents all" will be used. It means that the component with the worst condition will represent all the components of the same type; that is, for example, the most deteriorated pole will represent all the poles used in the feeder. This complies with the "dominant factor" discussed in [136, 137].

(2) *Translation of individual condition rating into overall condition rating*

Once the condition rating of each component which influenced by corresponding distress indicator is assigned, they would be aggregated towards their respective categories. Let $C_{i,j}$ denotes the condition rating of component j of category i and $W_{i,j}$ denoted the relative weight of each component contributing to its category, then it will be ended up with the aggregated contribution of the said category towards the final condition rating. The relative weight is dependent upon the role that the component plays in the degradation process and failure of asset category. These values are assigned by the domain experts.

If H_i denotes the aggregated condition grade of category i, then H_i is given by:

$$H_i = [W_{i,1}...W_{i,j}...W_{i,N_i}] \bullet [C_{i,1}...C_{i,j}...C_{i,N_i}]^T \qquad (5.30)$$

where N_i represents the number of components in category i .

Relative degree of significance is then assigned in the same manner to aggregate categories towards the overall condition rating. W_i denotes the relative weight of category i towards the overall condition rating; the aggregation process is given by:

$$C = [W_1...W_i...W_M] \bullet [H_1...H_i...H_M]^T \qquad (5.31)$$

Where M is representing the number of asset category and C is 5-tuple fuzzy set representing the condition rating of asset. In the same manner, the weight values are established through expert opinion.

Table 5.10 illustrates the feeder asset and relative weight as assigned by utility experts.

Table 5.10 Distribution feeder asset components categories and their relative weights as specified by utility experts

Category	***i***	**Weight (W_i)**	**Component**	**i,j**	**Weight ($W_{i,j}$)**
Pole structure	1	5	Pole	1,1	4
			Crossarm	1,2	3
			Guy	1,3	3
			Fittings	1,4	3
Conductor assembly	2	5	Conductor	2,1	5
			Insulator	2,2	5
			Splice	2,3	3
Lightning protection	3	2	Overhead ground wire	3,3	3
			Lightning arrester	3,2	5
Circuit protection	4	8	Fuse cutouts	4,1	3
			Switch	4,2	5
			Recloser	4,3	3

(3) Adjustment of the condition rating to a practical format using defuzzification

It would be more realistic if the condition state of a certain asset contains only two contiguous states. This would comply with intuitive expert opinion, e.g. an expert would unlikely assign a condition grade to an asset with the positive membership value to, say, good and poor at the same time. If the fuzzy set C obtained from (*2*) has support (non-zero membership values) to more than two contiguous states, adjustment is needed in the following manner. First, condition rating C is defuzzified into crisp value. Then, re-map this crisp value on the universe of discourse of fuzzy set C. For example, if the fuzzified value of C yield a fuzzy set (0.019, 0.687, 0.250, 0.044, 0), it can be re-mapped and yields (0, 0.681, 0.319, 0, 0)

5.4.3 Asset Deterioration Model and Future Condition Rating

After some times in service, the asset deteriorates to a certain level. This might be caused by the slow natural ageing mechanism or by rapid degradation under extreme stress. The future condition for any asset is the result of degradation processes that evolve probabilistically. In particular, this means that once an asset enters the worst degradation condition, it stays there for all future time. Furthermore, assume that at any transition, the asset condition can move only to the neighboring worse condition; conditions cannot be passed over; then the Markov transition matrix takes on this particularly simple structure. In practice, the determination of state transition probability which represents the deterioration rate of asset in this case is however difficult to obtain; this usually relies on expert judgment to specify this Markov transition matrix [139]. In this thesis, the determination of state transition probability is not main topic of research work; it is thus obtained using a very simple calculation just to show the application of Markov deterioration process in determining the future condition grade of considered asset.

Practically, under the same condition and environment of service, if the controlled (maintenance) actions are not performed, the rate of condition degradation of asset should remain the same. In addition, if the asset is assumed to degrade from brand new to failed condition in linear fashion along its life expectancy then we can simply compute the yearly base deterioration rate by the followings. If *Y* is assumed to be life expectancy of asset in years and there are *n* condition grades that asset should possess (figure 5.8); the asset would spend *Y*/(*n*-1) years to completely transition from its original state to next contiguous state. Therefore, it can be said that the asset loses its memberships of belonging to current state by (*n* -1)/*Y* per year. For example, if the life expectancy of the distribution feeder is 40 years and it has 5 condition grades (*good* to *failed*) and current state is *good* (for example); then the feeder would completely lose its *goodness* to *adequateness* in 10 years or, on the other hand, it can be claimed that this feeder loses its memberships of belonging to *good* state by 10%. This means, every year the said feeder loses 10% of its *good* grade to *adequate* grade.

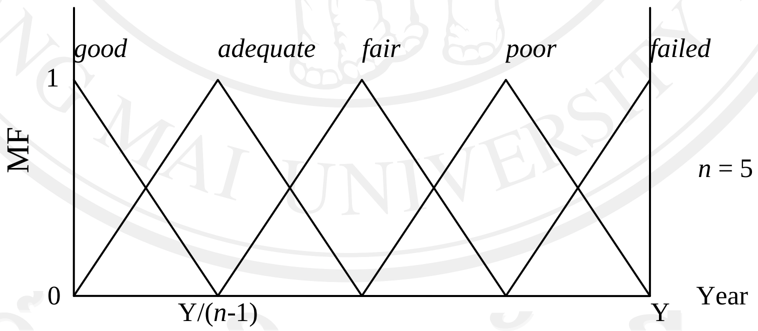


Figure 5.8 Distribution of asset condition grade along its entire age

Based on above assumptions, if two condition grade of a certain asset which obtained from reasonably time-distant interval are known, the system can then be trained to compute the expected deterioration rate which in turn able to form Markov transition matrix and predict the future condition. In doing so, the serviced age of the asset, the condition grade as well as deterioration rate are partitioned into their corresponding fuzzy sets. The typical fuzzy sets of age (*A*), condition grade (*C*), deterioration rate (*D'*) and fuzzy rule set (*R*) are shown in figure 5.9-11, and table 5.11 respectively. This is done through a domain expert guidance. Please note that the deterioration rate *D'* is mapped onto a dynamic relative scale that ranges from 0 to $2d_o$, where d_o is the base deterioration rate and has the underlying units of fractions of membership per year which obtained as explained above. It shall be noted that under the design operating condition and environment the feeder component shall be operable till the end of its design life; so the rate of $2d_o$ is arbitrarily assumed for the fastest deterioration. It is also worth noting that the failed condition grade is an 'absorbing' state which is when the asset entering this state it will remain in this state forever.

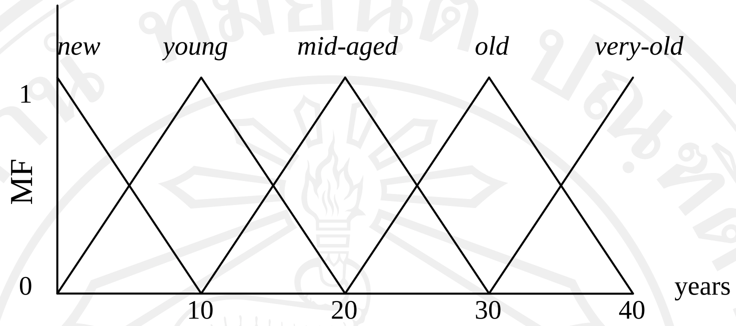


Figure 5.9 Fuzzy sets of asset age

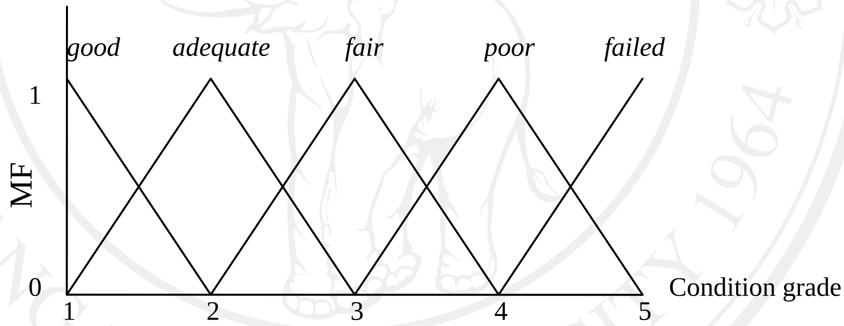


Figure 5.10 Fuzzy sets of asset condition grade

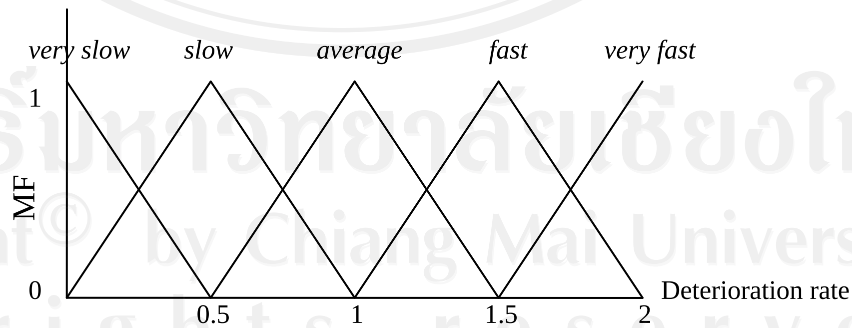


Figure 5.11 Fuzzy sets of asset deterioration rate

Table 5.11 Fuzzy inference rules for Markov deterioration model

Deterioration Rate (*D'*)	**Condition Grade (*C*)**				
Age (*A*)	***good***	***adequate***	***fair***	***poor***	***failed***
new	average	fast	fast	very fast	very fast
young	average	average	fast	very fast	very fast
Meddle-aged	slow	average	average	fast	fast
Old	very slow	slow	slow	average	fast
Very old	very slow	very slow	slow	average	average

The obtained deterioration rate will indicate the possibility of future state, hence if present state is known, then the future state could be predicted. This falls into the concept of Markov chain of which behavior of a system that moves from one state to another state in a way that depends only on the current state [140]. It is thus, for the certain asset, the relation between number serviced years, the condition grade and deterioration rate can be formed as:

$$D_t^{'} = (A_t \wedge C_t) \circ R_D \tag{5.32}$$

where o is a max-min composition operator [111], A_t are fuzzy sets of asset age at evaluated time *t*; C_t are fuzzy sets of condition grade at evaluated time *t*; and R_D are fuzzy inference rules that derive the fuzzy set of deterioration rate D'_t, as depicted in table 5.9 above. Let denote D_t the defuzzified (crisp) value of D'_t , the condition rating of asset in the next time step C_{t+1} could be calculated from its condition rating in the current time step, C_t, and the crisp deterioration rate D_t obtained by rule-base algorithm in the current time step as follows:

$$C_{t+1} = C_t \otimes D_t \tag{5.33}$$

Where the operator $\otimes$ can be described as a simple matrix multiplication between row matrix of membership of each condition state at time *t* and square deterioration rate matrix at time *t*. However as already discussed above, two assumptions have been made in order for the derivation in (5.33) being practicable. First, it is reasonably assumed that an asset cannot improve itself without any intervention. Second, it is assumed that the deterioration process is continuous and slow relatively to the selected time step, therefore, an asset in state *i* can at the most deteriorate to state *i*+1 within a single time step. Therefore, equation (5.33) can now be written in a matrix form:

$$(\mu_{t+1}^{C_1},\ldots,\mu_{t+1}^{C_5}) = (\mu_t^{C_1},\ldots,\mu_t^{C_5}) \otimes \begin{bmatrix} 1-D_t^{1,2} & D_t^{1,2} & 0 & 0 & 0 \\ 0 & 1-D_t^{2,3} & D_t^{2,3} & 0 & 0 \\ 0 & 0 & 1-D_t^{3,4} & D_t^{3,4} & 0 \\ 0 & 0 & 0 & 1-D_t^{4,5} & D_t^{4,5} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (5.34)$$

Where $\mu_{t+1}^{C_i}$ is the membership value to condition state i. The deterioration rate matrix in the RHS of (5.34) is analogous to a transition probability matrix in the traditional Markovian deterioration process. If, for example, $D_t^{i,j} = 0.1$, it means that the asset loses 10% membership to state i in favor of state j ($j = i + 1$) as it transits from time step t to $t + 1$.

This system needs at least two condition states of different time interval to train the deterioration model. The elemental one is the asset condition immediately after installation which can be assessed or assumed with simplicity. The others can be obtained using the technique discusses in the previous section. However, the behaviour of traditional Markov process tends to distribute the condition grades of asset to more than two contiguous states; this would contradict to the expert intuition. Therefore the adjustment of condition grade as described in previous section should be preformed.

The overall architecture of asset deterioration model is graphically illustrated in figure 5.12 below. The distress indicators are inputs of the fuzzy synthetic evaluation engine (FSE) which in turn produces a present condition of an assessed asset. This present asset condition is then brought to fuzzy inference system (FIS) to determine the deterioration rate of an asset. The initial asset condition, i.e. the condition at the stage of commissioning, as well as asset service age are also needed to train the deterioration model. Finally, with the application of Markov chain (MC), the future asset condition could be predicted.

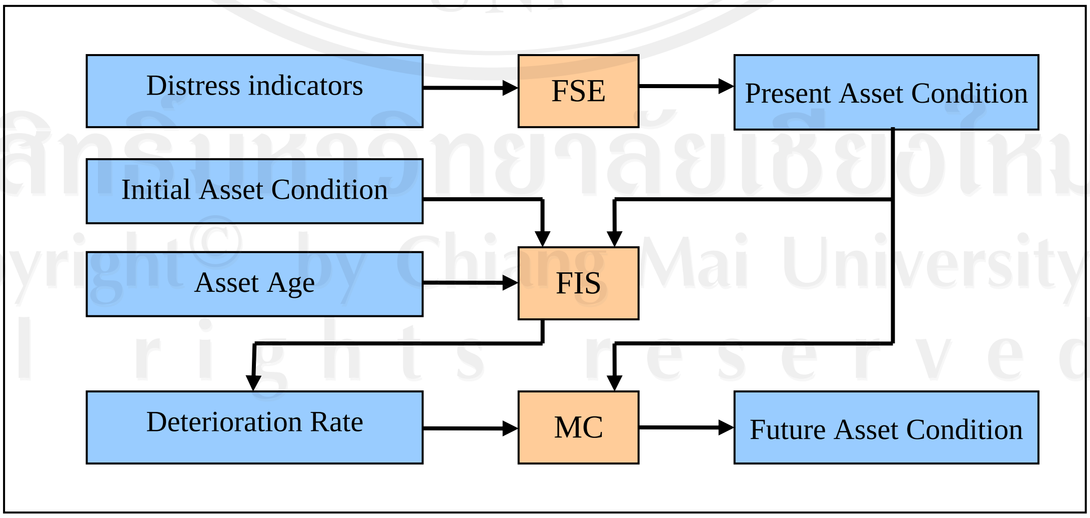


Figure 5.12 The overall architecture of asset deterioration model

5.4.4 Determination of Feeder Failure Possibility

The performance of distribution asset depends greatly on its intrinsic property, operational condition and external environment. In previous section, the asset condition grade which is regarded as a representation of intrinsic property was discussed. In this section, the asset stressors will be taken into consideration. Stressors are external influences that may increase the likelihood that a distribution feeder and its components will fail. The definition of a stressor is arbitrary. The present implementation of the asset management methodology decision framework identifies two kinds of stressors, environmental and operational stressors [139]. Generally, environmental stressors represent factors that are beyond the control of the utility, such as moisture or weather conditions, while operational stressors represent factors that are potentially within its control, such as feeder loading. Manipulating a condition grade possessed by the asset with stressors that the asset encounters by means of evaluation technique, the failure possibility of such asset can be determined.

In [141], the application of fuzzy reasoning process for evaluating risks in underground distribution networks has been demonstrated. It has shown that this technique worked effectively with this kind of evaluation. Therefore, this technique is used as a main methodology in the proposed evaluation system for distribution feeder failure. To evaluate the likelihood of the failure, both the asset condition grade and stressors are taken into evaluation in fuzzy inference system (FIS); they are then manipulated against some preset criteria represented in the forms of inference rules to determine such failure posibility. The architecture of proposed FIS is shown in figure 5.13.

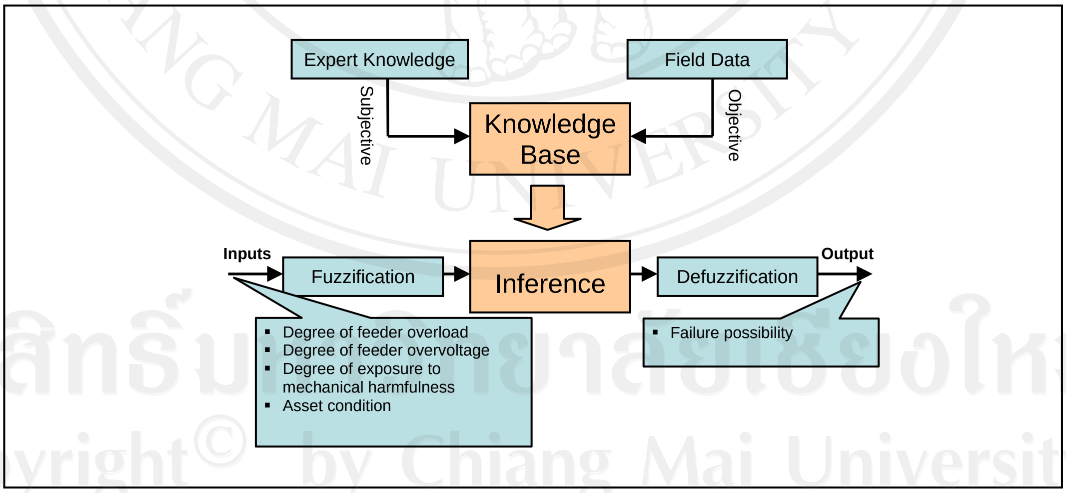


Figure 5.13 Fuzzy Inference System (FIS)

The steps for failure possibility evaluation include:

(1) Identify the failure event and its driving causes, and then formulate linguistic variables related to such driving causes; these linguistic variables will represent inputs to the FIS. Furthermore, linguistic variables for output, e.g. failure possibility, are also formulated.

(2) Categorize the input linguistic variables into group of relevance in order that

the evolution process can be done in stage-wise manner.

(3) Fuzzify the data associated with each linguistic variable to form a fuzzy set.

(4) Establish the fuzzy inference rules to deduce the output from various input data.

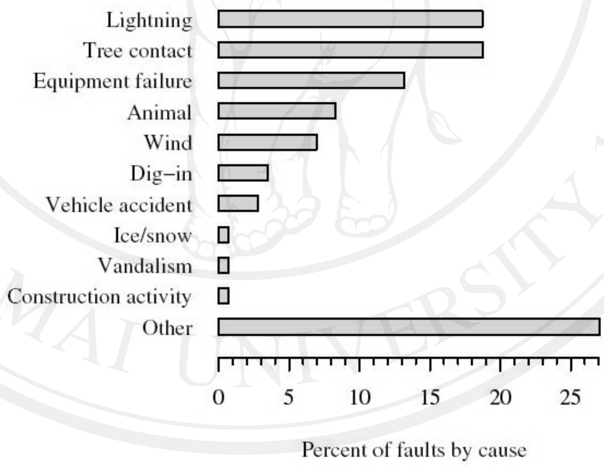
(5) Defuzzify the output fuzzy set to obtain a single crisp value of failure possibility.

(6) Translate the failure of the feeder into a practical measurable term, i.e. money value.

The detailed procedure of all six steps will be described as the followings. Knowledge engineering approach is employed in developing this failure assessment procedure.

(1) Identify failure causes and related linguistic terms

In order to define the linguistic terms related to the distribution feeder failure, the failure events and their associated causes must be firstly identified. There are many events that result in the failure of feeder. According to EPRI study [142], the events that resulted the distribution feeder faults were driven by major causes shown in figure 5.14.



Data sources: Burke and Lawrence[55], EPRI 1209-1[56]

Figure 5.14 Fault causes measured in the EPRI fault study

Most of these failure events are the results of external environment stressors which are somehow beyond the control of utility. When incorporated the contributions from operational stressors and component intrinsic properties into the equation, it will thus make the failure assessment of distribution feeder comprehensive and robust. At the beginning of section 5.5, modes of failure that the distribution feeder must have experienced which include thermal, voltage, and mechanical failure have been addressed. Employing all these knowledge, feeder evaluation forms that will address the important information bodies required for assessing distribution feeder failure which are later used to determine the failure possibility can be developed. It thus makes data collection on the assessed feeder easy accomplished.

But first, it might be helpful to learn what utility engineers shall look for when they are assessing the distribution feeder failure. As stated earlier, the distribution feeder comprises of various components of which may be impacted by stressors in different ways and may fail in different forms. The followings are addressing the failure problems and associated causes based upon the group of components.

Pole Structures

Steelwork faces rust problems. Failure of wooden poles may be in the forms of rot, decay, infestation, splits, breaks, or burns which, apart from natural deterioration process, mostly caused by birds nesting, wood pecker, and termites. Cracking and separation on surface of concrete pole are due to the moisture seeping inside to contact the reinforce steel. The integrity of all crossarms is jeopardized by rust, rot, twist, or rotating which make these crossarms break, split, crack, or detach from the pole. Guy line failure may appear in forms of worn, frayed, or broken wires or detach from the pole. All of these will eventually cause pole and its structure to lean, break, detach or even collapse, inhibit the pole structure to perform its functions. Failure of the pole structure is also often originated from lightning, construction/ vehicular accidents or even animal rubbings.

Conductor Assemblies

Overhead conductors fail due to overloading by snow or ice, tree problems, high winds causing clashing and arcing, and fatigue from vibration. Aluminum conductor may also be weakened by corrosion. In most areas, trees or branches falling, blowing, or growing into lines is the single greatest cause of outages. High winds and ice are often associated with tree problems. In some areas, lightning may be the primary cause of overhead line failure. Lightning failures depend not only on the region and the level of thunderstorms, but the particular location of the line, such as an exposed hillside versus a valley, and the lightning protection from arrestors, insulators, use of overhead ground wires, level of grounding and soil moisture content. Failures in overhead joints and accessories are often caused by improper design or installation. Wind can induce vibration which leads to fatigue. Water has negative effects on both cable and cable joints. In particular in aluminum joints, water can react with the aluminum to create a gas, and the gas pressure can cause joints to fail. The major sources of insulator breakage problems involve with dust deposited on the surface, animal, lightning or even shooting. Theft on metal parts is also causing problems to utilities.

Lightning Protection Devices

The mostly used techniques for lightning protection are arrester and overhead ground wire. During normal operating condition arrester acts as an insulator (high resistance component) to distribution feeder; only it turns to a low resistance path under the presence of overvoltage voltage. The cause of arrester problems is more or less similar to those for an insulator. Both of arrester and ground wire must be properly installed in order that the feeder will be appropriately protected.

Circuit Switches

Corrosion is a major problem with switches used outdoors. If wind driven rain can enter joints and assemblies, corrosion problems are exacerbated. Bi-metallic corrosion has also been known to cause problems with contacts. Rodents and other small animals are a problem due to nesting in pole-mounted and pad-mounted equipment.

Animal Damage

Look for any signs of animal damage such as bite or chew marks or nesting materials. Also make note of any sign of animal-induced flashes and any animal carcasses that appear to have fallen from the line.

Storm Damage and Out of Spec Construction

Some storm damage may go unnoticed, particularly if it does not cause an interruption. Other times storm damage is repaired but those repairs may not meet construction specifications due to the unavailability of materials, time constraints, or out of town crews who are lending a helping hand. The line inspector should keep and eye out for storm damage and any construction (or repair) work that does not meet the construction specifications.

Vegetation and Right-of-Way

Tree can fail power lines in two ways: mechanical failure and electrical failure. In mechanical mode, it occurs when structural failure of the tree or parts of trees (branches) causes physical damage to energy delivery infrastructure. An example would be a tree taking down conductors, arms, and poles as it falls. In electrical mode, the tree or parts of the tree provides a short circuit fault pathway between areas of unequal electrical potential. An example would be a branch lying between energized phases. In this failure mode, the electric system infrastructure typically remains intact.

Inspector should note any areas of obvious or impending vegetation growth into the conductors as well as any trees that may allow a person to climb to a point at which they could contact the line. Unchecked vine growth can quickly cover poles and spread along the conductors. Also note danger tress that may fall onto the line. Note any excessive vine growth on poles and equipment. The inspector should also make note of any other right-of-way deficiencies including encroachments by foreign structures, damaged or missing company gates, fences and signs, and limited structure access.

Above discussion addressed the failure events occurring on the distribution feeders. Employing the knowledge discussed above, the feeder operational and environmental stressors evaluation form can then be developed. These forms articulate the linguistic variables being derived from the events. Furthermore, they also assist inspectors to easily identify the possible defects, damages, negative signs that may occur in the feeder components. The full set of such evaluation forms as well as linguistic variables are published in appendix A3.

(2) Categorize the input linguistic variables

The fuzzy inferencing process for failure possibility assessment can be done in multiple steps. Since it is not a single thought process; rather reaching the final result is a combination of decisions and each information is assessed on its own merit then forwarded to another decision making operation. This process is done in stage wise manner [143]. The most important difference with respect to the traditional approach is the inclusion of intermediate stages to combine a number of parameters using fuzzy reasoning. This makes the decision process a more human-like procedure.

In order to serve the stage wise evaluation process, the linguistic variables obtained from previous section have to be categorized into group of relevance. That is, the failure modes discussed in the section 5.3.1 can be employed as guidance for grouping. However, the intermediate stage, i.e. the output of each group must be introduced and then forwarded as an input to the next stage.

As shown in figure 5.15, the thermal group contains electric load current, ambient temperature and ventilation capability which influenced by either wind speed or refill media depending on whether overhead or underground facility. The output of this category is the thermal violation degree. Another group involves with the voltage related matters, i.e. the lightning exposure, lightning protection and pollution. The output is the voltage violation degree. Voltage violation leads to the occurrence of flashover (discharge). The pollution intensity is placed in this category due to its tendency make the insulator deposited with dust or other polluted substances with in turn degrade its voltage withstand capability and consequently cause flashover. Similarly, the tree exposure, accident exposure and animal involvement form the mechanical category. Mechanical contact tends to provide a low resistance path between live parts or from live part to earth, especially in case of bare wires, causing sudden to the feeder. For example, if trees make contact with live part of feeder it will then suddenly originate a short circuit. The output of this group indicates the degree of mechanical contact. Consequently, all three outputs from thermal, voltage and mechanical stressors are collectively assessed to form the influential degree of these stressors. On the other hand, this degree indicates how significant the feeder is violated by operational and external stressors from the level it is designed for. In the final stage, the degree of stressors, operational and external influencers, and feeder condition grade, intrinsic influencer, are assessed the likelihood of feeder failure can then be estimated.

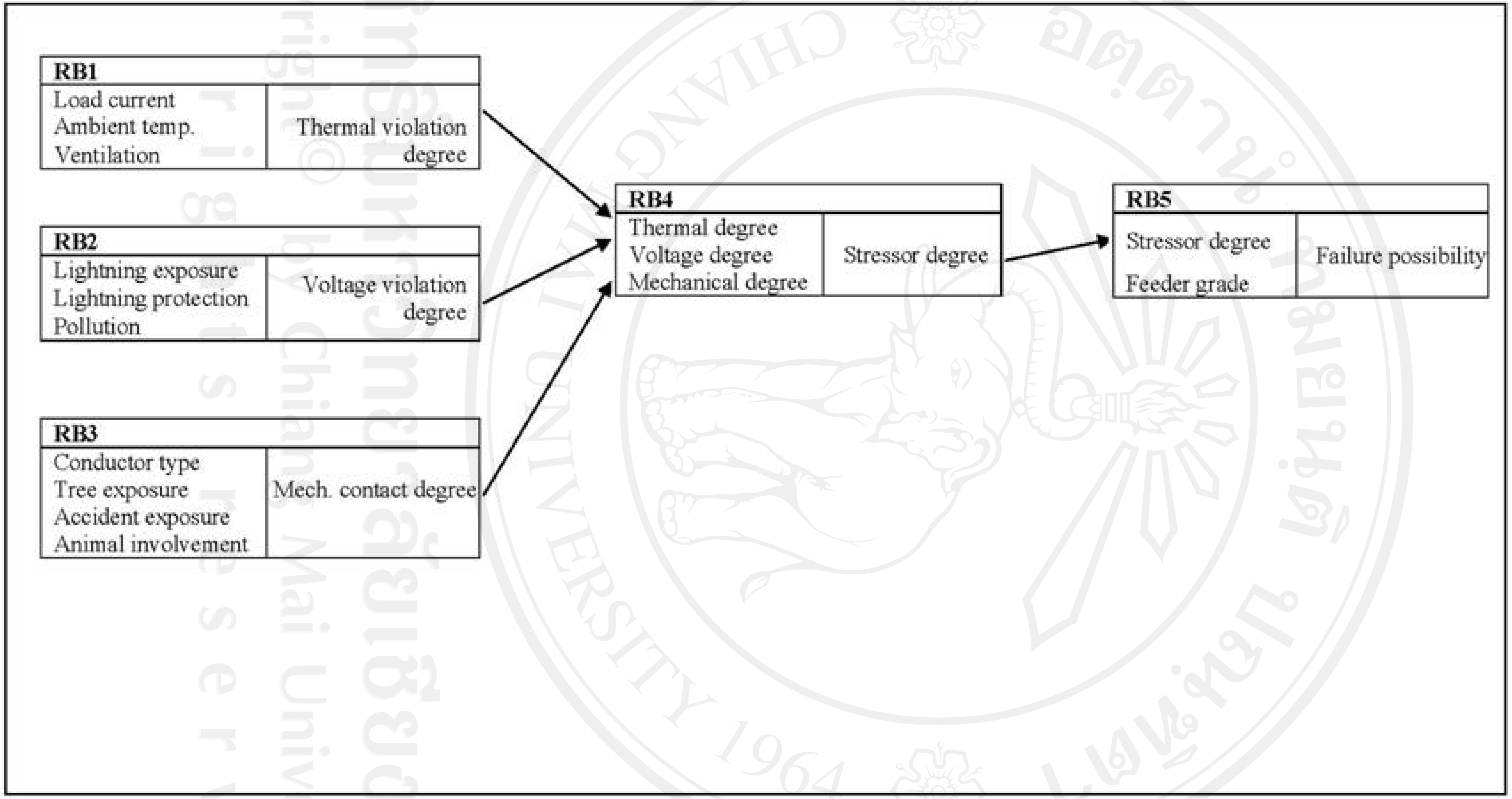


Figure 5.15 Stage wise fuzzy reasoning process

(3) Fuzzify the data associated with each linguistic variable to form a fuzzy set.

Fuzzification of linguistic variables is done with intuition, experience and judgment of utility experts on how significant each input variable contributes to the output attainment. Linguistic values are used to form fuzzy sets of each variable. For example, the terms *very low*, *low*, *medium*, *high and very high* can be used to represent these linguistic values. Based on a rule of thumb, the entire range of universe of discourse is partitioned into intervals with equal length and the triangular membership function is used to characterize the input and output fuzzy sets respectively. The triangular function is used based on the fact that membership function of each fuzzy set at any point in the input/output domain is summed to unity. Furthermore, the triangular function for the output variable to aid in the speed of the defuzzification calculation [98]. The membership functions of input and output variables can be formulated as shown in table 5.12.

Table 5.12 General idea of the fuzzy sets of linguistic variables

Linguistic Fuzzy Sets	**Triangular MF** $f(x:a,b,c)$		
	a	*b*	*c*
Very low value	-	0.00	0.25
Low value	0.00	0.25	0.50
Medium value	0.25	0.50	0.75
High value	0.50	0.75	1.00
Very high value	0.75	1.00	-

It shall be noted, except otherwise specified, that the universe of discourse of each linguistic variable is confined in range of [1, 5] of which the lower number indicates the lower degree of linguistic terms and the higher number indicate the higher degree.

Table A3-1 – A3-9 in Appendix A3 illustrate the fuzzy sets of all input linguistic variables shown in figure 5.18, while table A3-10 – A3-14 indicate the output fuzzy sets.

(4) Establish the fuzzy inference rules

The basic function of inference rule is to represent the knowledge of an experienced utility expert in the form of *IF-THEN* rules. Similarly to the previous discussion of deterioration rule base establishment, the derivation of the rules is accomplished by examining the experience based knowledge resided in linguistic variables. This provides an initial set of rule base and consequently tuning of the membership functions and the rules may be necessary.

The evaluation process is executed in the stage wise manner; this not only makes the evaluation more human-like but also let the numbers of rules decreased considerably. Consequently, it also helps reduce the computation speed. Table 5.13 illustrates the rule base for the determination of the failure possibility by taking into consideration the mechanical contact degree and the feeder behavior from the previous stages. The rule bases for other evaluation will be summarized in Appendix A4.

Table 5.13 Fuzzy rule base for failure possibility determination

Feeder failure possibility		**Stressor degree**				
		very low	**low**	**medium**	**high**	**very high**
Condition grade	**good**	*very low*	*low*	*medium*	*high*	*very high*
	adequate	*very low*	*low*	*medium*	*high*	*very high*
	fair	*very low*	*low*	*medium*	*high*	*very high*
	poor	*very low*	*low*	*medium*	*high*	*very high*
	failed	*very high*	*very high*	*very high*	*very high*	*very high*

(5) Defuzzify the output fuzzy set to obtain a single crisp value

The realization of fuzzy inference process from step 3 till this step (step 5) can be implemented using the fuzzy logic toolbox of MATLAB [144]. MATLAB provides visual interfaces for creating linguistic variables, assigning memberships function to each of them, establishing inference rules, and finally defuzzifying the output in accordance with preset input linguistic variables. MATLAB also allows the users with possibility to use Mamdani or Sugeno inference techniques. And the Mamdani method is used in thesis.

As stated earlier however, the fuzzy inference process is done in stage-wise manner, so the crisp output from previous stage will be used as input for next stage. Finally, the failure possibility of distribution feeder can be obtained from system and represented as a single crisp value.

(6) Translate the failure into a practical measurable term

The failure possibility represents the percentage that the feeder is likely to fail if it continues to operate under ongoing stressors. As well, if the feeder actually fails it costs something to both customers and utility. The expected failure cost can then be simply calculated by multiplying these two numbers together. For example, if the failure possibility computed from the proposed system is 70% and the costs borne by both stakeholders are 2,000,000 Baht then the expected failure cost for this example is 1,400,000 Baht. The process of failure cost evaluation will be thoroughly discussed in chapter 6.

5.4.5 Combining Together

The overall architecture of risk assessment engine for distribution feeder which thoroughly discussed is shown in figure 5.16.

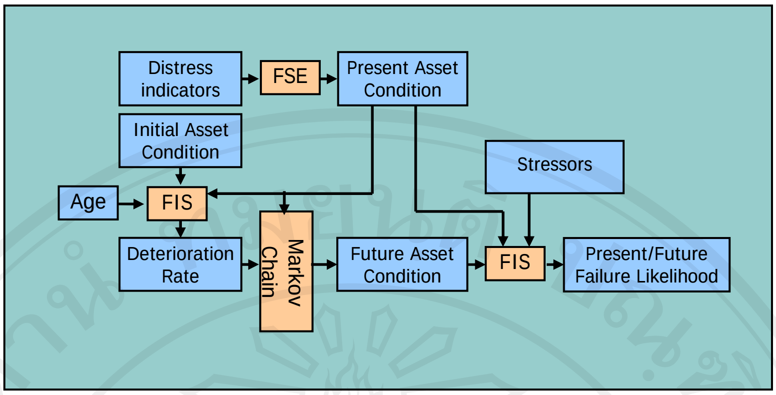


Figure 5.16 Risk assessment engine for distribution feeder

It starts with the assessment of feeder condition rating or grade. This is done by examining the distress indicators shown on each feeder component. Distress indicator is a sign of deterioration that component has undergone during year-long operation of feeder which in turn indicate the condition grade of such individual component. Using the method of fuzzy synthetic evaluation (FSE), the overall feeder condition grade can eventually be concluded. The risk module is however designed to predict the feeder condition rating along its operating life by employing the Markovian deterioration process. In doing so the deterioration rate of feeder asset needs to be evaluated first. This can be achieved through fuzzy inference system (FIS) taking into account known asset condition rating of different time instance to train the FIS. The deterioration rate represents the degree that asset loses its membership of current state to next contiguous state per year. It will then be used to formulate a transition matrix which in turn used to calculate the future grade of the remaining years.

The failure of distribution feeder depends on two main driving factors: feeder asset condition grade and operation and environmental stressors. Condition grades are derived from distress indicators as mentioned above while stressors are derived from the contributing factors that cause feeder to thermally overload, electrically (voltage) breakdown or mechanically collapse. If the feeder is highly deteriorating, it is likely to fail even though the stressors are not taking parts. Conversely, although the feeder is brand new but if stressors are extremely high, the feeder would be likely to fail as well. The crisp value of risk module output indicates the percentage of the feeder failure occurrence per km length per year.

In this chapter, all the issues related to the distribution feeder failure have been addressed and the failure possibility assessment system was then proposed. The percentage of feeder failure possibility computed using the proposed framework will be transformed into quantifiable terms (monetary value) using the methods discussed in the next chapters. The case studies to show its applicability will be illustrated in the following chapters.