Fuzzy Knowledge Based Reliability Evaluation and Its Application to Power Generating System

Wang, Lei

Fuzzy Knowledge Based Reliability Evaluation and Its Application to Power Generating System

A thesis presented by

Lei Wang

in partial fulfilment for

the degree of

Doctor of Philosophy

of the

University of London

Department of Electronic Engineering

Queen Mary and Westfield College

London E1 4NS

July 1994

ABSTRACT

The method of using Fuzzy Sets Theory(FST) and Fuzzy Reasoning(FR) to aid reliability evaluation in a complex and uncertain environment is studied, with special reference to electrical power generating system reliability evaluation.

Device(component) reliability prediction contributes significantly to a system's reliability through their ability to identify source and causes of unreliability. The main factors which affect reliability are identified in Reliability Prediction Process(RPP). However, the relation between reliability and each affecting factor is not a necessary and sufficient one. It is difficult to express this kind of relation precisely in terms of quantitative mathematics. It is acknowledged that human experts possesses some special characteristics that enable them to learn and reason in a vague and fuzzy environment based on their experience. Therefore, reliability prediction can be classified as a human engineer oriented decision process. A fuzzy knowledge based reliability prediction framework, in which speciality rather than generality is emphasised, is proposed in the first part of the thesis. For this purpose, various factors affected device reliability are investigated and the knowledge trees for predicting three reliability indices, i.e. failure rate, maintenance time and human error rate are presented. Human experts' empirical and heuristic knowledge are represented by fuzzy linguistic rules and fuzzy compositional rule of inference is employed as inference tool.

Two approaches to system reliability evaluation are presented in the second part of this thesis. In first approach, fuzzy arithmetic are conducted as the foundation for system reliability evaluation under the fuzzy environment. The objective is to extend the underlying fuzzy concept into strict mathematics framework in order to arrive at decision on system adequacy based on imprecise and qualitative information. To achieve this, various reliability indices are modelled as Trapezoidal Fuzzy Numbers(TFN) and are proceeded by extended fuzzy arithmetic operators. In second approach, the knowledge of system reliability evaluation are modelled in the form of fuzzy combination production rules and device combination sequence control algorithm. System reliability are evaluated by using fuzzy inference system. Comparison of two approaches are carried out through case studies.

As an application, power generating system reliability adequacy is studied. Under the assumption that both unit reliability data and load data are subjectively estimated, these fuzzy data are modelled as triangular fuzzy numbers. fuzzy capacity outage model and fuzzy load model are developed by using fuzzy arithmetic operations. Power generating system adequacy is evaluated by convoluting fuzzy capacity outage model with fuzzy load model. A fuzzy risk index named "Possibility Of Load Loss" (POLL) is defined based on the concept of fuzzy containment. The proposed new index is tested on IEEE Reliability Test System (RTS) and satisfactory results are obtained

Finally, the implementation issues of Fuzzy Rule Based Expert System Shell (FRBESS) are reported. The application of FRBESS to device reliability prediction and system reliability evaluation is discussed.

ACKNOWLEDGEMENTS

The thesis and the research described in it could not have been achieved without the help of my supervisor, Professor M. A. Laughton, whom I gratefully acknowledge. I am indebted to him for his patient supervision, constant advice and encouragement, and financial support during the research work.

Most of all, my special thanks are due to my wife, Dr. Xiao-Lan Wang, and my parent and parent-in-law for their dedicated support and encouragement in all I have undertaken.

CONTENT

Chapter Five : Application Of Fuzzy Reliability Techniques To Power Generating System

Chapter Six: Implementation Of Fuzzy Rule-based Expert System Shell (FRBESS) For Reliability Evaluation

Chapter Seven: Conclusion

List of Figures

List of Tables

Chapter One

INTRODUCTION

1.1 Introduction

The ultimate output of any system is the performance of some intended function. This function may be described by some system output characteristic, such as satisfactory supply to meet load demand in a power generating system. The term often used to describe the overall capability of a system to accomplish its mission is system effectiveness. The system effectiveness relates to the property of system output which is the real reason for buying the system---namely, carrying out of some intended function. Of the major attributes of determining system effectiveness, the one that received the most thorough and systematic study in recent years is reliability.

Since World War II, the reliability problem has become so acute in designing complex systems such like space shuttle, nuclear station etc., for the reason that the failure of these systems will result in severe consequences. Therefore, the traditional deterministic (qualitative) reliability evaluation can no longer meet the requirement of modern reliability evaluation. The quantitative reliability evaluation is needed . All techniques of reliability evaluation are concerned with future behaviour of a component or system. The time scale of future behaviour may vary between a matter of seconds, or several decades. Hence, the reliability problems are defined as stochastic in nature, i.e., it varies randomly with time. Probability theory has been brought into the area of reliability evaluation, because the complete assessment of a stochastic process can only be achieved using probability techniques. Since then probability techniques has gained its unshakeable stand in quantitative reliability evaluation, as a matter of fact , modern reliability is defined under the name of probability.

The challenge to the stand of rprobability theory in reliability evaluation came from two directions: (1) The size and complexity of modern systems have increased so rapidly. The relationships among its subsystems and components become more uncertain. (2) the number of emerged system evaluation data increases rapidly. It becomes more difficult to obtain these data objectively in terms of using statistical method. The human experts' judgement play more and more important role in decision making, including reliability evaluation.

1.2 The Uncertainty Problems in Reliability Evaluation

Probabilistic approach to reliability evaluation are based on the premise that probability theory provides the necessary and sufficient tool for dealing with the uncertainty which underlies the concept of reliability in decision analysis.

This premise has been questioned[12,43,46,58,67,79]. Uncertainty arises in many forms in reliability evaluation. Traditionally, uncertainty is modelled based on randomness only. However, recently fuzziness uncertainty has caught more and more attention in reliability evaluation. The trend in current engineering application is to combine the subjective (human expert judgement) and the objective (statistically obtained) information together to yield an optimal decision which should be as close to reality as possible.

The required human observations, descriptions and abstractions during the modelling process are always a source of imprecision. A way to classify this imprecision that leads to uncertainty or, in case of vague descriptions, to fuzziness is described in figure 1.1[76]. In reliability evaluation, the most often occurred situations in acquiring an objective data from the data base can be concluded as: (1) insufficient; (2) unavailable.

The analysis of system overall performance by means of reliability is of evaluating the reliability indices[4,10]. Hence, A system reliability index depends on the components reliability index. The component reliability index is often regarded as basic

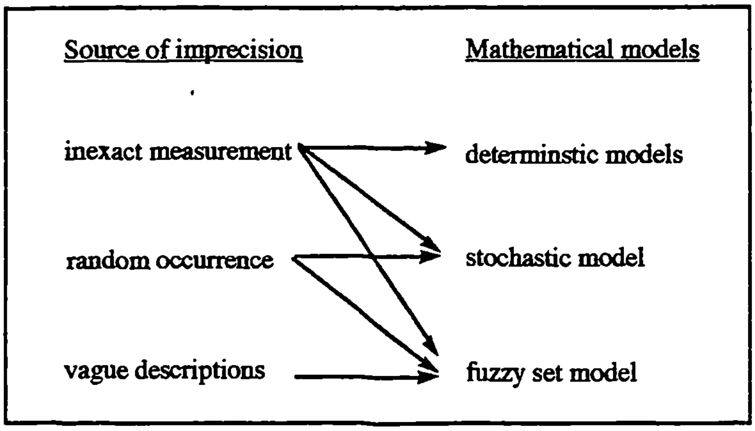


Figure 1.1 Mathematical Models For Imprecision

index, or 'root' index. .In reliability evaluation, these root indices are usually obtained from:- (1) laboratory test such like stress test; (2) past operating records. These data must be collected by the utilities concerned for a reasonable length of time before any meaningful conclusion can be made from them. However, this is not easily met requirement in various situations mainly because of:- (1) system complexity. If a system is large and complex, there appear various failure modes, and it is difficult to define an event precisely [70].Hence it is difficult to collect appropriate data; (2)the probabilistic repetitiveness underlies in the collected data about the system behaviour. Especially when the effect of environmental factors and human behaviours are considered. e.g., software debugging processes [69]; (3) the sample size of collected data. In many situations there are only few data available. e.g. in the astronautica area only a few space shuttles have been built thus only a small size of samples is available.

According to the probability theory, however, the term "probability" makes sense in reality if and only if the following premises are satisfied:-(1) a precisely defined event; (2) a precisely defined probability distribution of the collected data ; (3) a large size of the sample data. As these premises are not encountered, the term "probability" makes nonsense and therefore any calculated reliability indices based on such premises may be completely mislead.

Certainly, there are many other uncertainty causes, however the most often occurred situation in planning and design stage, is that the unavailability of any statistic data. Consider a newly installed core device of a nuclear reactor, it has no previous service record, and it is too expensive to have it tested. Moreover, some reliability parameters, such like human operator's error rate and failure caused by environmental factors, are unable to obtain objectively---there has no certain probability distribution fitted human behaviours.

In the case of the lack of objective information, reliability evaluation is forced to depend upon the subjective estimation given by human experts. The functions performed by the reliability engineers in reliability data acquiring process are best described as[56]

"Task shall focus on the provision of information essential to acquisition, operation , and support management, including properly defined inputs for estimates of operational effectiveness and ownership cost...ensuring...efforts to obtain management data that is clearly visible and carefully controlled."

The human experts are able to give their judgement based on the past experiences and by comparing the similar equipment. Even in the case that there are some objective data available but are not sufficient, the subjective estimation given by the experienced engineers can be the complement and contrast to the objective data.

However, there are two major difficulties for human being to make the judgement. They are the complexity of the studied system and its inherent imprecision. The overall environment of a system, for example a nuclear plant, is a complex arrangement of dependent interlocking events. The cognitive overload on a person who must estimate some important quantitative data for the entire system is staggering. More often than not, a human being is forced to neglect a set of data. Unfortunately, this can result in the ignoring of data ultimately important to the overall result, thereby providing a sub-optimal (or even a totally wrong) estimation. Such a wrong estimation can be both costly and dangerously.

On the other hand, even if the problem due to complexity was solved, the other problem of inherent imprecision remains to complicate the task of estimation. Suppose that one is asked to estimate the probability of a component failure, the estimation given is as "the probability of the component failure is 0.01" is very precise. However, if the exact probability is something like 0.011, the estimation given is completely false.

The problem with the precise estimation of the probability of a component failure is that it possesses only a pseudo-accuracy---it looks great to the casual observer, but it fails to take into account perturbations that are possible in the real world---perturbations that are in some sense likely, taking into account Titantic effect: "If something can possibly go wrong, they will; if they can not possibly go wrong, they still will". These real-world events are ignored in the "precise" analysis because it is unrealistic to estimate the probability of a component failure---there just is not and never will be sufficient data for such a mathematically precise estimate. In fact, the word "sufficient" itself is a subjective measurement and has great fuzziness. Therefore, all one can reasonably estimate is the possibility of such an event taking place, given the information that one can have on hand or can reasonably assemble. Realising this inherent lack of precise and complete data, it would seem (at least at first glance) that rather than estimating the probability of a component failure as 0.01, it is really more accurate to say that the failure probability is "approximately 0.01". In making this replacement of "approximate 0.01" for a crisp value "0.01", we are sacrificing the "precision" of the numerical estimate to gain the believability and confidence of an inexact, "fuzzy" estimate that is both more realistic and easier to interpret. The limitations of subjective estimate can be overcome to some degree if Fuzzy Set Theory and Fuzzy Reasoning are employed, as they are shown in the later chapters of this thesis.

1.3 The Current Approaches To the Problem Solving

As the fact mentioned above that the source of information is mainly human being---that implies the information is imprecise, incoherent, and in any case is incomplete. Because of this, the technique for representing these imperfect information, and of the methods for handling them, plays a substantial role in the reliability analysis.

Developing a technique to handle the subjective information, the first attempt was using the probability theory. On contrast to the objective probability , there is the so called "subjective probability", which tried to avoid the difficulties of the concept of frequency encountered in applying the theory (sufficiently many observations, repeatability of experiments, and so on) by proposing probability as a measure of the feeling of uncertainty. The numerical value of a probability is then interpreted as a proportion to the sum an individual would be willing to give should a proposition that he asserts proved false. For example, the proposition like " probability of tomorrow will rain is 0.5" implies that there is half chance that "tomorrow will not rain". However, when the proposition becomes "probability of tomorrow will rain is likely 0.5" either objective and subjective probability turn out to be inadequate to deal with the situation. It seems to offer too normality of a framework to take account of subjective judgement. This point has been well discussed among references [20,65].

A commonly known subjective probability technique is Bayesian method. Bayesian technique involves the use of probabilities, which is only natural, since the probability is thought of as the mathematical language of uncertainty. Two concepts are used in this technique: prior probability and posterior probability. A prior probability is first given subjectively for the truth of a proposition. When new information is available, the prior probability is then updated to give the posterior probability of the proposition by using Bayes aggregation formula[24].

Bayesian method has been successfully applied to represent and process uncertainty in an expert system called PROSPECTOR[25]. An expert system is regarded as the embodiment within a computer of a knowledge-based component, from an expert skill, in such a form that the system can offer intelligent advice or take an intelligent decision about a processing function. A knowledge based system is an expert system except that its knowledge level may not be regarded as expert skills. In a knowledge based approach with a new architecture centred around a "knowledge base" and an "

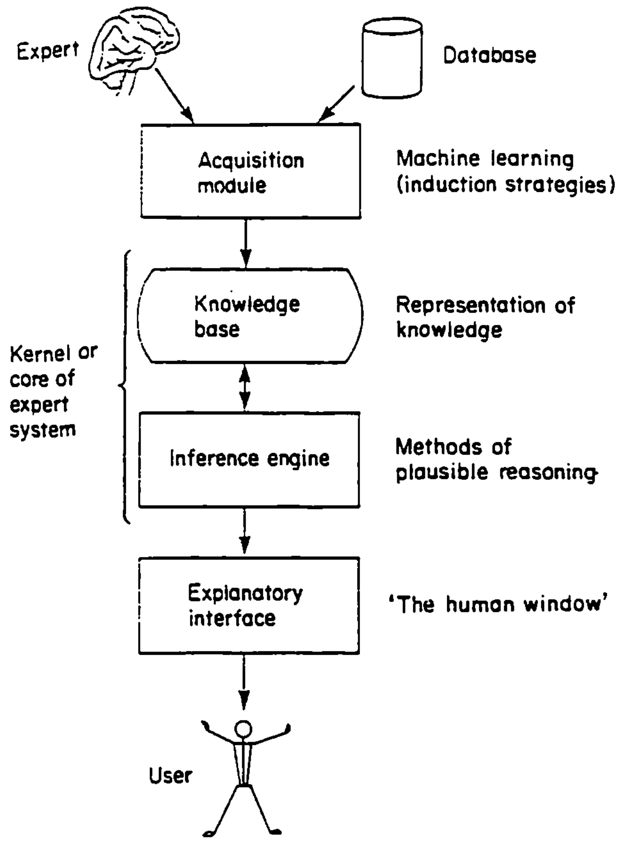


Figure 1.2 Structure Of A Typical Expert System

---

inference engine", the problem solving strategy will replace the software tradition of "data+algorithm=program" by " knowledge+inference=system".

Any knowledge based system , from the pioneer MYCIN by Shortliffe in 1976[78] to the latest one. will inevitably encounter with the uncertainty problem in its knowledge acquisition. representation and reasoning processes[31]. Many methods have been proposed and developed to handle the uncertainty in a knowledge based system. The most commonly known methods are single value represented Bayesian and certainty factor Shortliffe methods. two bounded values represented Dempster-Shafer method, and many values represented fuzzy reasoning method.

1.4 The Proposed New Approach

As it has been stated in section 1.2 that much of the uncertainty which is intrinsic in reliability analysis is rooted in the fuzziness due to the fact that many reliability source data are estimated subjectively by human experts. Viewed in this perspective, then it is not satisfactory to apply classical probability theory to reliability analysis which is under the fuzzy environment, as it has been discussed in the previous section.

The newly emerged Fuzzy Set Theory (FST) calls into question the validity of applying probability theory to an area where the subjective information is dominated[80,94]. Initiated by Zadel in 1965[92], FST has been developed as a specialised branch of modern mathematical theory which can handle the vague concept and soft data. The application of FST to the various subjects , such as industrial control, electronics production, decision support system etc., has gained overwhelming success. In Japan it has caught fuzzy logic fever[48] in recent years. New products ranging from auto-focusing cameras to hovering helicopter, from industrial assembly line to Japan's fastest train, are using fuzzy control algorithm alone. Table 1.1 gives a list of products utilising fuzzy logic. Not only in Japan alone, FST has gained more and more attention in many countries. A report described how "fuzzy thinking" works was published on the recent issues of the Economist (see figure 1.3).

In applying the theory of fuzzy set and possibility to the analysis of real world problems, it is natural to adopt the view that imprecision in primary data should, in general, induce commensurate imprecision in the results of the analysis. It is basically this view that motivated the introduction of the concept of a linguistic variable, that is, a variable whose values are not numbers but words or sentences in a natural or synthetic language. The theory of fuzzy sets provides a framework for dealing with such variables in a systematic way and thereby opens the door to apply fuzzy knowledge based techniques to reliability analysis.

By using FST, and the concepts and techniques of its two important extensions: fuzzy reasoning and fuzzy arithmetic, the new proposed approach to reliability evaluation is presented in the following chapters of this thesis. The objectives of the conducted works are as the following:

Products utilizing fuzzy logic

Product	Company	Role of fuzzy logic
Elevator control	Fujitec/Toshiba	Evaluates passenger traffic to reduce waiting time and enhance car announcement accuracy
Golf diagnostic system	Maruman Golf	Selects best golf club for an individual's physique and swing
Video camcorder	Sanyo Fisher/Canon	Determines best focus and lighting when several objects are in picture
Washing machine	Matsushita	Senses quality and quantity of dirt, load size, and fabric type, and adjusts wash cycle
Vacuum cleaner	Matsushita	Senses floor condition and dust quantity and adjusts vacuum cleaner motor power
Hot water heater	Matsushita	Adjusts heating element to correspond to temperature and amount of water being used
Air conditioner	Mitsubishi	Determines optimum constant operating level to prevent power-consuming on-off cycling
Television	Sony	Adjusts screen brightness, color, and contrast
Handheld computer	Sony	Interprets handwritten input for data entry
Auto transmission	Subaru	Senses driving style and engine load to select best gear ratio
Stock trading program	Yamaichi Securities	Manages stock portfolios

<u>**Table 1.1 List of Some Products Utilising Fuzzy Logic**</u>

---

(1) The source of uncertainty in reliability evaluation shall be explored in depth. The human reliability engineer's knowledge of acquiring the reliability source information shall be studied and such knowledge shall be properly organised and represented in the form that it can be processed by an inference engine.

(2) The research shall be conducted from the root level of a system analysis. In reliability evaluation, it is to study reliability of each individual components (devices) in the system, and explore the source of imprecision of devices reliability index.

(3) The reliability engineer's knowledge of acquiring data, analysing system configuration and processing devices index to evaluate a system reliability shall be studied and modelled in order to develop a knowledge based reliability evaluation model.

(4) Such knowledge based model shall be able to evaluate system reliability under the circumstance that some, or all reliability source index are fuzzy data. Therefore, the proposed knowledge based system shall be regarded as an fuzzy inference system.

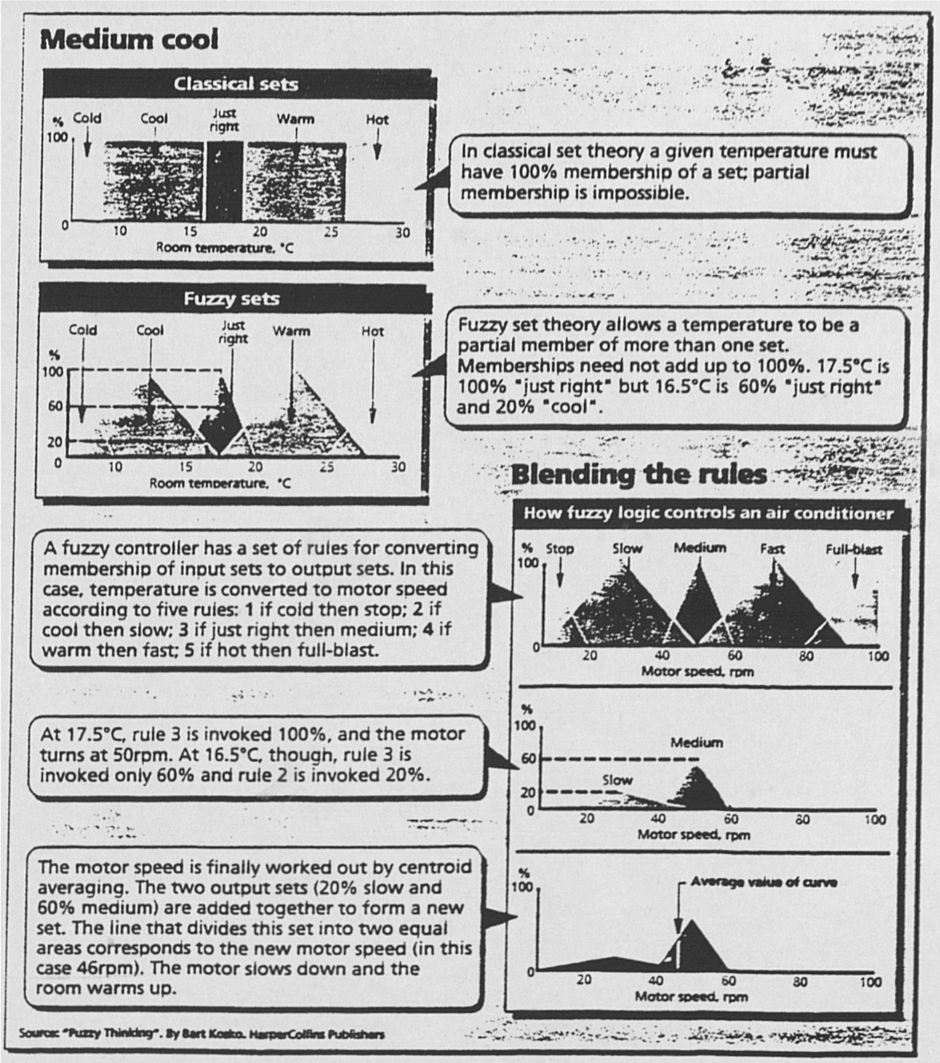


Figure 1.3 Demonstration Of How "Fuzzy Thinking" Works (Quota From The Economist)

(5) The proposed system shall be able to offer maximum flexibility for human experts to contribute their knowledge. Hence, a linguistic based knowledge representation and inference mechanism shall be considered.

(6) The proposed reliability evaluation method shall be extended to one of real industrial application, such as power generating system reliability evaluation to test its applicability.

1.5 Structure of Thesis

Chapter 2 briefly reviews some important concepts and techniques of probability reliability evaluation. The concepts like component and system are distinguished. The role of reliability indices is discussed. The basic techniques and procedures of reliability prediction are presented underlying the names of its three sub-tasks, i.e., device failure prediction, device total maintenance time prediction and human operator error prediction. The speciality consideration, that is, affects of situational factors on device reliability performance are emphasised.

Chapter 3 further discusses the relationship between the situation factors and device reliability performance. Some commonly emerged situational factors are identified and their relationships with predicting reliability index are presented in the knowledge tree form. The task of prediction is divided into two integrated parts: the basic estimation and the adjustment by affecting situational factors. Based on these, a fuzzy knowledge based model is developed to predict device failure possibility, device total maintenance time and human error possibility. The prediction rules are represented as IF-THEN fuzzy production rule format. The inference mechanism is developed based on fuzzy compositional rule of inference method. A case study is conducted in order to discuss and describe the performance of the proposed model.

Chapter 4 is concerned with the methodology of combining the inferred individual device reliability index to yield a system reliability criteria. Two approaches are presented. In the first approach the concepts and techniques of fuzzy arithmetic are employed. Fuzzy reliability index is modelled(or converted) as a parametric fuzzy number. By using fuzzy arithmetic operations the probability reliability combination rules are extended to fuzzy reliability domain and some fuzzy reliability index are defined. Fuzzy system reliability can be calculated by using these fuzzy reliability combination operations. In the second approach, a fuzzy knowledge based system reliability evaluation model is developed. Device reliability index is modelled as a fuzzy subset labelled by a linguistic term defined on a finite discrete universe of discourse. Fuzzy reliability combination rules are represented in fuzzy production rule format and reasoning sequence is controlled by a specially designed algorithm. Two cases are studied in order to discuss the performance of both approaches.

In chapter 5 the proposed fuzzy reliability evaluation techniques are extended to power generating system reliability evaluation. Both generating units reliability data and load data are modelled as triangular fuzzy numbers. Using the concept of fuzzy containment, fuzzy generating capacity model and fuzzy load model are convoluted to give a fuzzy system risk criteria. A new fuzzy generating system reliability index is then defined as Possibility Of Load Loss. The RTS system is conducted to test the proposed new index.

Finally, chapter 6 describes the modules of the programmed FRBESS(Fuzzy Rule-based Expert System Shell). The implementation aspects of fuzzy knowledge representation and inference are discussed. Algorithms for rule compilation, reasoning sequence control and information process are also illustrated.

1.6 Summary

This chapter is an introductory presentation in which the problem of uncertainty in reliability evaluation has been briefly discussed. It is concluded that the existing probability reliability evaluation techniques has grown out of the demands of modern technology and particularly out of the experiences in World War II with complex military system. The objectives of developing a new techniques have been pointed out, and the structure of the thesis has been outlined to give a coherent presentation of this research.

Chapter Two

Probabilistic Reliability Prediction - Concepts & Techniques

2.1 Introduction

In every day life, particularly in technical area people always have intuitive sense of reliability of the objects, say, when one is going to purchase a product he will expect that the product will be safe and reliable. A question which often arises is "how reliable will the product be during its operating life?". In nature, the consideration is based on the future behaviour of the product. This question can be answered, in part, by the use of quantitative reliability evaluation. In consequence a considerable awareness has developed in the application of such techniques in the design and operation of simple and complex systems.

The quantitative evaluation of the future behaviour of a product (or system) can be achieved using probability techniques, since the event of failure is defined as stochastic rather than as deterministic in nature, i.e., it varies randomly with time. For instance, reliability prediction is a part of the overall reliability assessment process which indicates future reliability performance quantitatively by means of using probability techniques. However, it must be pointed out that probability theory alone cannot predict the reliability of a system without a thorough understanding of this system, such as its design, the way it operates, the way it fails, its environment and the stresses to which it is subjected. It is in this aspect of reliability prediction that engineering judgement is paramount and no amount of probability theory can circumvent it. Probability theory therefore is only a tool available to the engineer in order to transform his knowledge of the system into a prediction of its likely future behaviour.

The basic principle and procedure of general reliability prediction model are illustrated in this chapter. For this purpose, The underlying reliability prediction is defined as it carries out through its three sub tasks: device failure prediction, device maintainability prediction, and human error prediction. The presentation of this chapter is not intend to be a rigorous mathematical discourse on reliability prediction nor is it intend to cover all aspects of relevant probability theory used in reliability prediction in a detailed mathematical manner. Rather, it is intend to outline the basic concepts in reliability predictions which will be intensively used in the thesis.

2.2 Basic Reliability Concepts and Assumptions

There are many variations on the definition of reliability but a widely accepted form[37] is as follows:

Reliability is the probability of a device performing its purpose adequately for the period of time intended under the operating conditions encountered.

From the definition one can see reliability of a device depend on four major factors: Probability, Adequate performance, Time, Operating condition. The probability of a device failure is in deference under various working conditions. The criterion of adequate performance is a matter of engineering appraisal and appreciation.

Reliability Prediction can be defined as the process of estimating adequate performance of a system either quantitatively or qualitatively by means of the available statistical information and the engineer judgement. Among its subtasks Device Reliability Prediction focus on the numerical index (normally through estimating its unreliability index) which shall indicates how often a device is out of service in given time period. For repairable system, Maintainability Prediction provides another quantitative index for indicating the length of time a device is out of service. Human Error Prediction, on the other hand, concerns the adequate performance of human operators when they are operating the device. Reliability prediction contribute significantly to a system's reliability through their ability to identify source and cause of unreliability. The primary purposes of reliability prediction are of 1) identify cause and effect of unreliability 2) predict components and system reliability (or unreliability) either quantitatively or qualitatively. 3) provide useful reliability information for feasibility evaluation. Reliability allows action, maintenance and logistics planning.

2.2.1. The Concept of System, Component and Their Failures

Before approaching to prediction, it is necessary to define the term "component" and "system", as well as the relationship between component and system failure.

The term "component" is defined as that from studied object viewpoint it is a physical device at the lowest of hardware level of a system and it is not further dividable. A system is a collection of components physically jointed together in such a manner that, collectively, they perform a desired function or functions. If a system is capable of satisfactory performing and it functions at the same point of time, it will continue to have that capability until a significant change occurs in the operating characteristics of some components, or a group of components. If component failure is said to occur when the characteristics of as component, or a group of components, have changed to the point where they exceed the limits within which the system functions are satisfactorily performed, it is apparent that the system will fail whenever a component fails and conversely, whenever the system fails, one or more components must have failed.

The relationship between component and system failure has been established. it is evident that the reliability of a system is determined by the number of components it comprises and by the reliability of these individual components. One of the basic problem is predicting the reliability of a system, then, is determining the expected reliability of the individual components- as they are applied in the system.

Within the definition of component failure stated previously, the reliability of a component is determined by three facts: 1) the characteristic of the component at the beginning of the operating period of interest, 2) the characteristic limits which constitute failure, and 3) the magnitude of the change occurring in three factors could be determined for every component in a system prior to each period of operation, reliability could be predicted precisely. In fact, the ability to predict individual failure as implied here, suggests that all failures could be prevented with a resulting system reliability of 1.0. Unfortunately, it is not possible to determine these factors for individual components. To do so, it would require complete knowledge of the physics and chemistry of all failure mode and in addition, it would involve a monumental task of analysis and computation[37].Therefore, the usual approach to predicting reliability, and the approach proposed in later sections, is necessarily simpler and less rigorous that suggested by the preceding discussion.

For simplicity, the word "device" is used in this thesis in referring to all individual components which are at the lowest hardware level of a system.

2.2.2 Definition of Failure Probability, Reliability and Maintainability

The best known and probably the most frequently used expression in reliability engineering is the probability of a device surviving a given time period provide the device is in normal operating period.

In general, the devices of a system can be divided into two categories: repairable and unrepairable devices. The unrepairable devices are those which no longer be able to put back to service after their first failure. Respectively, the repairable devices are those which be able to put back to normal service after their failure, providing they have been properly repaired. The criterion for these two type devices is different in definition.

An important index for studying unrepairable devices is the surviving time of device from starting service to first failure, T. The surviving time of a device is in relation to many factors: materials, manufacture process, installation process and operation condition. Therefore, the surviving time of a device is a non-negative stochastic variable and it can be determined by its.probability distribution.

The distribution function of a device surviving in general is called failure probability function F(t). It is defined as the probability of devices surviving time equal or less than t. In other words, it means the probability of device fail from starting service to time t. It can be expressed mathematically as

$$F(t) = P[T \leq t], t \geq 0 \qquad \text{eqn 2.1}$$

This is a cumulative Probability Distribution Function (CDF). Similarly, the probability of a device surviving time greater than time t is called the Reliability Function of Device, R(t). R(t) can be defined as the function of time, that is,

$$R(t) = P[T > t], t \geq 0 \qquad \text{eqn 2.2}$$

obviously, R(t) and F(t) has the relation

$$R(t) + F(t) = 1 \qquad \text{eqn 2.3}$$

Another important index to measure the repairable devices reliability is the so called maintainability M(t). It is defined as the probability that a failed system is restored to operable condition in a specified down time t when maintenance is performed under stated conditions. M(t) can be expressed mathematically

$$M(t) = P[T \leq t], t \geq 0 \qquad \text{eqn 2.4}$$

2.2.3 Reliability Prediction *via* Basic Reliability Indices

It has been stated in the preceding section that Reliability of a device is defined as the adequacy of the product to perform the specified function in the designed environment for a minimum length of time or minimum number of cycles or events. Such adequacy is measured numerically as a probability, so that the probability is the first index of a device reliability.

The "life" of an individual device cannot be determined except by running or operating it for the desired time or until it fails. Obviously, one can not wear out all the products to prove that they meet the specifications. This in turn means that the statements regarding reliability must be in terms of probability of surviving the specified life with satisfactory performance throughout. However, in practice it is very difficult to derive probability distributions directly. Instead, reliability is normally stated *via* one or more reliability indices (parameters) which are used as the criteria of adequacy for the different applications. For example, Loss of Load Expectation is used to measure the adequacy of generating capacity to meet load, and Mean Time to Failure can be used to measure the adequacy of a computer software to serve users. Many of these reliability indices are

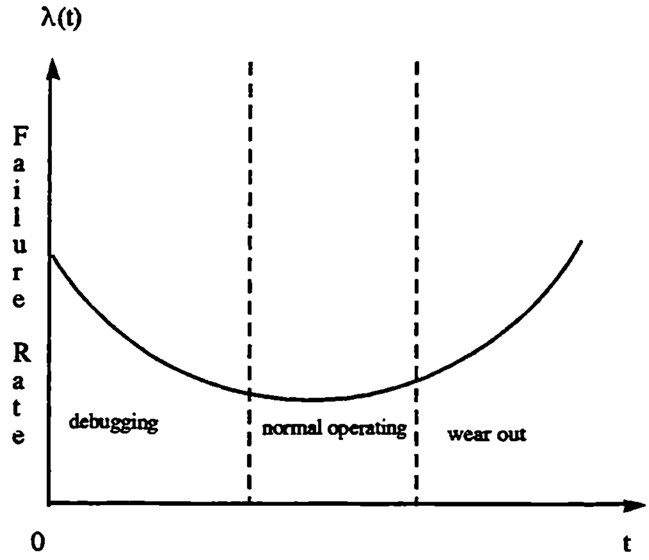


Figure 2.1 A Typical Failure Rate Curve

defined and used in reliability applications. In general, these indices take forms such as:- (1)Probability measure, e.g. reliability and availability. (2)Frequency measure, e.g. failure rate and repair rate. (3)Time measure, e.g. Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR). (4) Expectation measure, e.g. Loss Of Load Expectation (LOLE).

Reliability Indices are defined to indicate reliability performance of a device, and are used to measure the performance quantitatively. The number of indices required to measure performance sufficiently varies and is determined by the application to which a device is subjected. In general, for unrepairable devices, one index such like failure rate is enough to measure the extent of a device reliability adequacy for normal operation, but for repairable devices, in addition of failure rate, MTTR must be considered as well to give a complete reliability assessment.

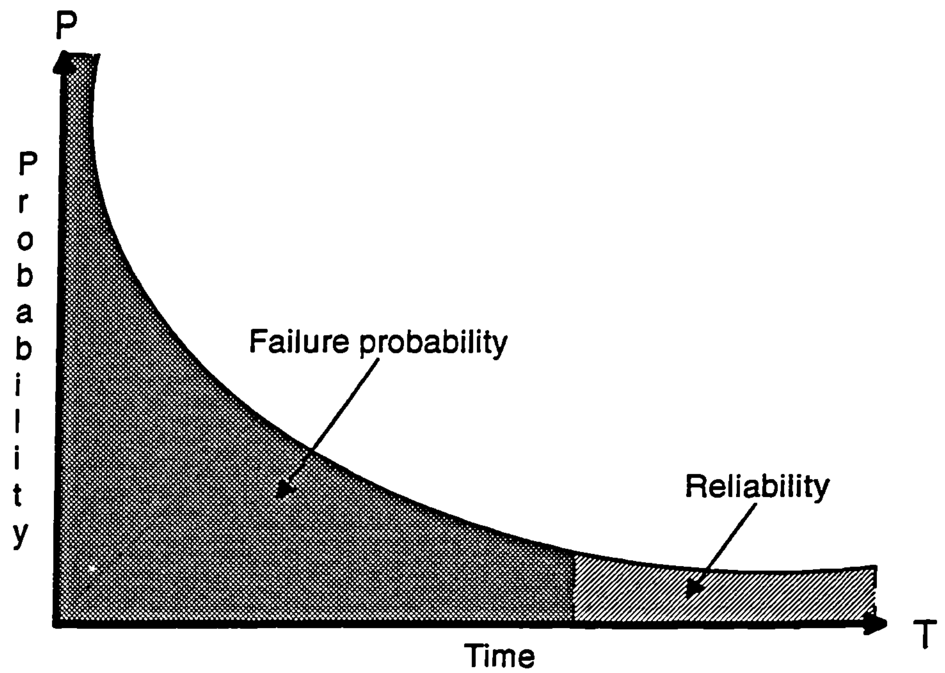


Figure 2.2 Reliability and Failure Probability With Constant Failure Rate

Among various reliability indices there are some indices which are accessible, measurable. and are used in the most cases. also from them other indices can be derived. This type of indices are the so called "basic reliability indices" . Among them Failure rate and Mean Time To Repair are the most important basic indices in reliability analysis.

Failure rate $\lambda(t)$ is defined as the conditional probability density of a device surviving before time t, failure in units of time after t. It can be expressed as

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P[t < T \le t + \Delta t | T > t] \qquad \text{eqn 2.5}$$

It is clear to see that the smaller the $\lambda(t)$, the smaller the probability of a device failure during the time interval $[t, t+\Delta t]$, and vice versa. Therefore, failure rate $\lambda(t)$ is an adequate index for measuring device reliability. Failure rate $\lambda(t)$ of a device will increase, stable or decrease respectively to various operating time periods. This is shown graphically in

Figure 2.1 and is often referred to as the conventional bath tub curve. In reliability analysis, most of interests lie on normal operating state, in which the failure rate is treated as a constant and failure is assumed to occur purely by chance. In this thesis, unless otherwise stated, device failure is assumed due to random failure.

If failure rate is a time independent constant , then reliability and failure probability have exponential distributions. They can be determined using failure rate as

$$R(t) = e^{-\lambda t} \qquad \lambda > 0,\ t \geq 0 \qquad \text{eqn 2.6}$$

and

$$F(t) = 1 - e^{-\lambda t} \qquad \lambda > 0,\ t \geq 0 \qquad \text{eqn 2.7}$$

Figure 2.2 shows reliability and failure probability density function with constant failure rate.

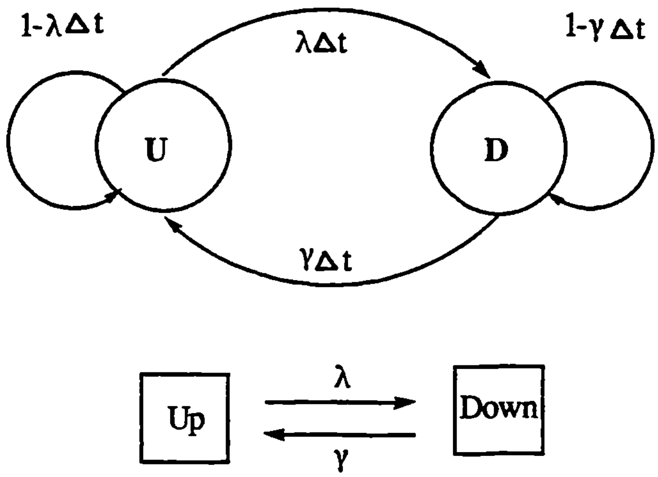


Figure 2.3 Two States Exchanges Diagram

A repairable device has two states during its service life, i.e., normal operation(UP) and out of age(DOWN) as illustrated in figure 2.3. In fact it has a constant failure rate, similarly to an unrepairable device being a constant during its normal operation stage. Besides, it has another index to measure the extent of maintenance and its effect, named repair rate γ (t), this is defined as

$$\gamma(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P[t < T_D \le t + \Delta t | T_D > t] \qquad \text{eqn 2.8}$$

where T_D is duration of device being repaired. If repair time T_D has exponential distribution, similar to failure rate, repair rate γ is a time independent constant. Therefore similarly to the case of failure probability, maintainability can be determined using repair rate γ as

$$M(t) = 1 - e^{rt} \quad \gamma > 0, t \ge 0 \qquad \text{eqn 2.9}$$

Although repair rate is an adequate index for predicting maintainability, the more popular index is MTTR rather than γ. MTTR is defined as the expectation of repair time T_D. If T_D has exponential distribution then the relationship between MTTR and γ can be derived as

$$MTTR = \frac{1}{\gamma} \qquad \text{eqn 2.10}$$

Once failure rate and MTTR are determined, other important indices can be derived from them. These indices include Mean-Time-Between-Failure (MTBF) for unrepairable devices, Availability and Unavailability for repairable device. Apparently, Reliability , Failure Probability and Maintainability are also determined. The relationship among indices are listed in Table 2.1. Briefly, apart from the probability, depend upon the system and its requirement there are many more reliability indices calculated and used. The term reliability is frequently used as a generic term describing all these indices rather than being solely associated with the term probability.

2.3. The Procedures of Traditional Probabilistic Reliability Predictions

This section outlines some basic concepts and the procedures of traditional probabilistic reliability predictions for device failure, maintenance and human operator error.

	Repairable device	Unrepairable device
Basic Relationship	$A(t)+Q(t)=1$ $A(t)>R(t)$ $Q(t)<F(t)$	$A(t)+Q(t)=1$ $A(t)=R(t)$ $Q(t)=F(t)$
Failure Process	$h(t)=\lambda$ $R(t)=e^{-\lambda t}$ $F(t)=1-e^{-\lambda t}$ $f(t)=\lambda e^{-\lambda t}$ $MTBF=\frac{1}{\lambda}$	$h(t)=\lambda$ $R(t)=e^{-\lambda t}$ $F(t)=1-e^{-\lambda t}$ $f(t)=\lambda e^{-\lambda t}$ $MTTF=\frac{1}{\lambda}$
Repair Process	$m(t)=\gamma$ $G(t)=1-e^{-\gamma t}$ $g(t)=\mu e^{-\gamma t}$ $MTTR=\frac{1}{\gamma}$	$m(t)=\gamma=0$ $G(t)=0$ $g(t)=0$ $MTTR=\infty$
Availability & Unavailability	$A(t)=\frac{\gamma}{\lambda+\gamma}+\frac{\lambda}{\lambda+\gamma}e^{-(\lambda+\gamma)t}$ $Q(t)=\frac{\lambda}{\lambda+\gamma}[1-e^{-(\lambda+\gamma)t}]$ $A(\infty)=\frac{\gamma}{\lambda+\gamma}=\frac{MTBF}{MTBF+MTTR}$ $Q(\infty)=\frac{\lambda}{\lambda+\gamma}=\frac{MTTR}{MTBF+MTTR}$	$A(t)=R(t)=e^{-\lambda t}$ $Q(t)=F(t)=1-e^{-\lambda t}$ $A(\infty)=0$ $Q(\infty)=1$

A(t): Availability
R(t): Reliability
h(t): Failure rate function
G(t): Repair probability
MTTR: Mean time to repair
λ: Failure rate
Q(t): Unavailability
F(t): Probability of failure
f(t): Failure density
m(t): Repair rate function
g(t): Repair density
MTBF: Mean time between failure
γ: Repair rate

Table 2.1 Relationships Among Reliability Indices

2.3.1. Device Reliability Prediction

The usual approach of reliability prediction, in general, can be divided briefly into four basic procedures as illustrated in Figure 2.4. These procedures are discussed under separate headings.

System and failure definition

The initial step in a reliability prediction is to define the system. The term "system" is used here to denote the particular collection of items to which a prediction pertains. The task of defining the system, then, consists of explicitly describing the functions and physical boundaries of the devices that constitute the system.

The term "failure" here is specified for the occurrence of any condition which renders the system incapable of operating with its specified performance parameter limits. The task of defining failure consists of listing or referencing the appropriate limits. This task normally carries out by either Failure Mode Effects Analysis (FMEA) or Fault Tree Analysis (FTA).

Construct Reliability Block Diagrams

A reliability block diagram may be considered as a logic chart which, by means of the arrangement of blocks and lines, depicts the effect of failure of devices on the system's functional capability. A sample reliability block diagram is demonstrated in Figure 2.7. Device whose failure causes system failure are showing in series with other devices, and device whose failure causes system failure only when some other devices have also failed are drawn in parallel with the other devices. The task in constructing a reliability block diagram can be done through either Failure Mode Effects Analysis (FMEA) or Fault Tree Analysis (FTA). The task is to determine the complexity levels of devices which are to be shown as separate blocks. Each separate blocks then is broken down to its first-order subdivisions. This process of diagramming goes on until individual block represents complexity of such an order that its reliability, or measures of unreliability such as failure rate, can be readily predicted from device level data.

Assign Preliminary Device Reliability (Unreliability) Measure

The procedure of estimate preliminary device reliability measures, e.g. failure rate consists two steps. The first step is to conduct a stress analysis to determine from design analysis, or measurement where possible, pertinent internal operating conditions like voltage, currents, power dissipation, etc., for each electronic device. Stress indices are then calculated through comparison of operating conditions with rated values. The next step is to assign failure rate, or other measure of reliability, to the individual devices. Two types of information are combined to obtain preliminary failure rate, namely, the basic

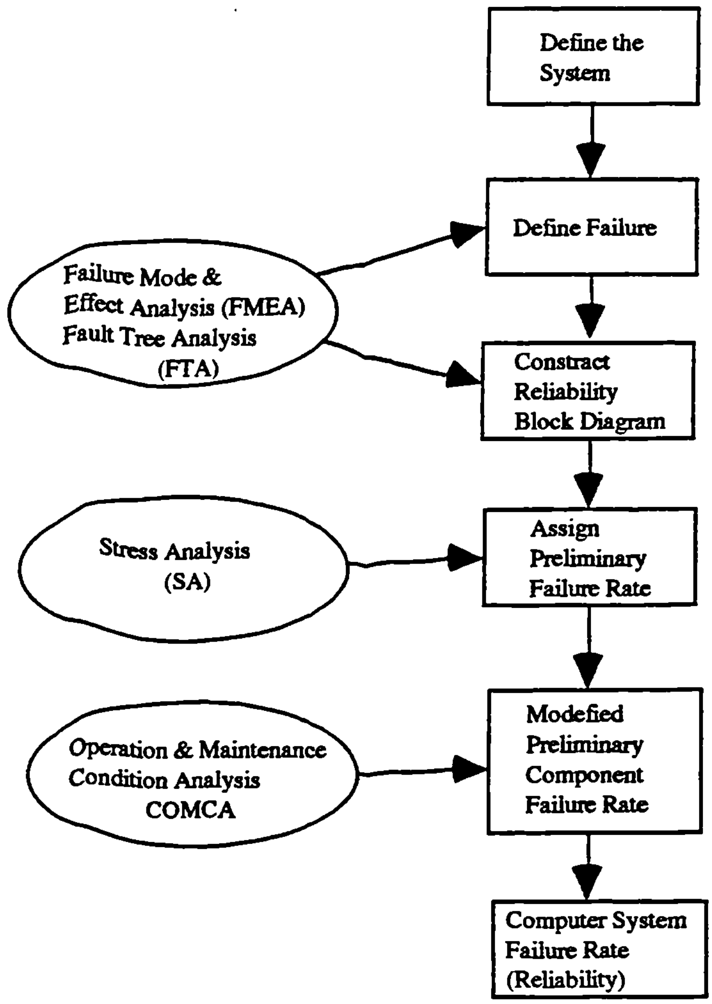


Figure 2.4 A General Device Reliability Prediction Diagram

failure rate and its stress adjustment rate of a device. The basic or standard failure rate is a strong function of stresses which reflects the device design and production quality. The data normally are obtained under the laboratory conditions, and are based on multi-million operating hours accumulated in dozens of different types of systems and are over a long term period. The basic failure rate is associated with some rated values such as the stress boundaries, operating conditions of the test from which the basic failure rate is obtained. Another type of information, the stress adjustment rate, determined in the preceding step. Preliminary failure rate therefore can be determined. One recommended method to obtain adjusted preliminary failure rate tasks the form of an equation similar to[4]

$$\lambda_n = \lambda_0 \prod_{i=1}^{n} k_i \qquad \text{eqn 2.11}$$

where λ_n is the adjusted preliminary block failure rate; λ_0 is the basic failure rate; k_i is the ith stress adjustment rate.

Modify Preliminary Device Reliability Measures

Preliminary failure rate is modified next to account for external environment conditions. These use condition adjustment factors are determined through Operation and Maintenance Condition Analysis (OMCA). The task of OMCA is to identify the conditions under which the product will be stored, handled, transported and used. OMCA should also include identification of possible misuse and maintenance practices. A product may be used in many different environments. For instance, consider a telephone equipment which could be placed in either the controlled environment of a centre office or in an open field where extremely high or low temperatures may affect its operation. Therefore, to predict reliability it must consider the different environmental factors to which the product will be exposed. These environmental factors, except some cases such as lunar surface operations, were obtained by comparing observed reliability with predictions. As far as the observed data are indicative, the values selected are proper adjustments for prediction of reliability that can reasonably be expected within the "design state of art" and with the use of devices comparable to those presently available.

Mathematically, the modification for environmental factors are treated similarly to the anticipated stress factors by multiplying its values on the pre-calculated preliminary failure rate. Thus, the formula for final failure rate is in the form of

$$\lambda_{nm} = \lambda_0 \prod_{i=1}^{n+m} K_i \qquad \text{eqn 2.12}$$

where λ_{mn} is the final adjusted failure rate; λ_o is the estimated basic failure rate; K_i is the ith factor , m and n are the number of stress and environmental factors.

Compute System Reliability

Once the failure mode is identified, the fault-tree analysis is completed, the device preliminary basic failure rate is estimated by considering basic failure rate suitably modified by anticipated electrical, thermal or other stress factors, and then further modified by suitable factors related to the anticipated system environment, the system reliability parameters can be estimated. System reliability is computed by entering individual devices reliability parameters into the system reliability formula and solving for the time periods or mission phases of interest. The detailed system reliability integration is further discussed in section 2.5.

2.3.2 Maintainability Prediction

In the evaluation of a repairable system, the measure of maintainability is quite important. How often the system fails (reliability) and how long it is down (maintainability) are vital considerations in determining its worth. In practice, the trade-off between these two concepts is dictated by lost, complexity, weight and operational and other requirement.

Mean Time To Repair is the most frequent used parameter for maintainability evaluation. In actual practice, however, it is to predict the total maintenance time for a device in a specified time period. MTTR is obtained if the total maintenance time and the number of maintenance time interval are known, for MTTR is defined as the mean of the total maintenance time. It can be expressed as

$$MTTR = \frac{\text{the total maintenance time}}{\text{the number of maintenance time interval}} \qquad \text{eqn 2.13}$$

The same result can be obtained by using mathematical expectation, in which another reliability index failure rate is used

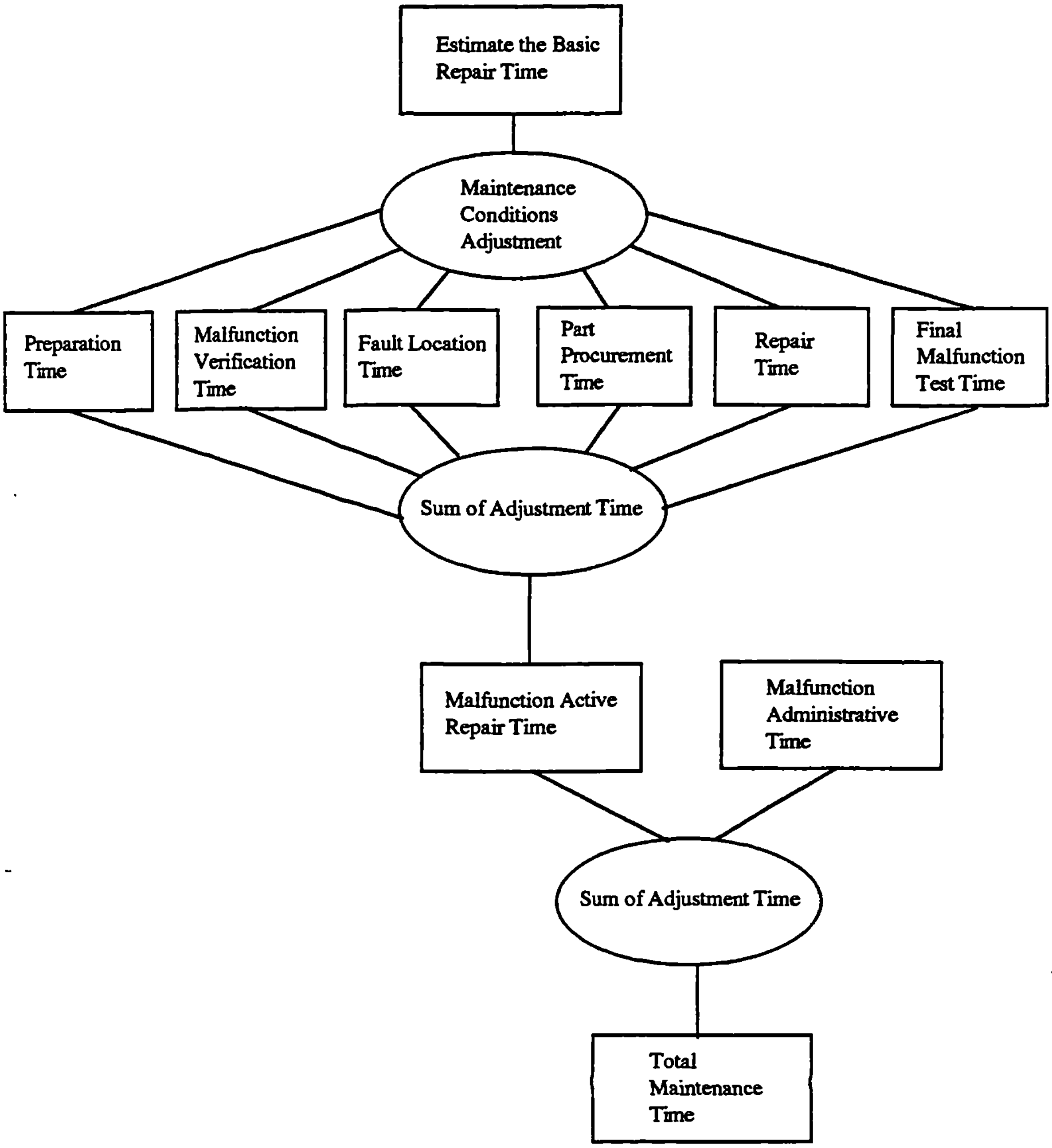


Figure 2.5 A typical Maintainability Prediction Diagram

$$MTTR = \frac{\sum_{i=1}^{n} \lambda_i t_i}{\sum_{i=1}^{n} \lambda_i} \qquad \text{eqn 2.14}$$

where t_i is the maintenance time of the ith interval. The concept in predicting devices total maintenance time is similar to the one in predicting failure rate. The prediction consists of two parts: a test or operational record based basic estimation of total maintenance time which reflects the allowable down time according to the design and production standard; and the actual maintenance condition adjustments. It was established that any maintenance action can be classified as one of the following categories:- (1) preparation. (2) Malfunction verification. (3) Fault location. (4) Part procurement. (5) Repair. 6) Final malfunction test.

The time required to perform each of these categories varies from zero to several hours, depending on numerous maintenance conditions associated with particular events, weather, for example, causes great variations in time required for preparation. Other adjustment factors include the skill level of maintenance personnel, their confidence and familiarity with the device under repair, and even manner in which symptoms are reported to them. This variability in performance time would limit the accuracy of any maintainability prediction based on statistic.

The procedures of device maintainability prediction is presented in Figure 2.5. The first step is to estimate the basic maintenance time in a time period, which is normally stated by the supplier according to design and production specifications. This basic maintenance time is adjusted thereafter in each maintenance categorised based on specified maintenance conditions to which a device is subjected. The sum of the adjusted maintenance time is the total malfunction active maintenance time. The final maintenance time is the sum of active maintenance time and adjusted maintenance administrative time.

2.3.3 Human Error Prediction

Human Error rate Prediction (HERP) is still in its early age though it has evolved over the years and seems to posses special interest to those involved in human error analysis and prediction. The Nuclear Regulatory Commission has given considerable emphasis to this technique in probabilistic risk assessment[37].

The current approach to HERP is mainly deterministic in nature and largely depends on subjective estimations. The basic tool in applying HERP methodology is a tree diagram representing the action taken by an device operator or maintenance to complete a task. Probability values are assigned to each successive sub task success or sub task failure branch in the tree. These probability values are compounded in accordance with the usual probability compounding principles to yield an estimate of human error probability for the task under analysis. The procedure is analogous to reliability determination for device on the basis of the reliability of the device.

One of the more interesting aspects of the technique is its incorporation of "performance shaping factor" [14]. These are operator or maintainer and environmental variables which influence the assigned probability of various points in the activity sequence. Human operator variables are of mental or cognitive aspects of task performance, such like competence, psychological stress, etc. Environmental variables are of working condition aspects such as human interface, workload, weather, space etc. These variables are treated as modifiers of complex human performance, and are determined in a set of empirical models which addresses the relationship between these variables and human performance by the correlation analysis. The final human error rate is determined by combining the modifiers and the assigned rate.

2.4 Speciality Considerations in Reliability Prediction

Speciality Considerations are embodied through stress factors, maintenance conditions and performance sharping factors which were discussed in the proceeding sections. The term "situational factor" [14] is defined as a generic term describing all these factors in this thesis.

Two concepts were permeated with reliability prediction: the basic estimation and the situational factors. In the conventional reliability prediction the basic estimation is calculated by human engineer based on the statistic method, therefore, the data is probabilistic in nature. The validation of basic estimation depends on sample size, time, data collection processing methodology of which a device is tested. The basic estimation reflects the generality of device or human reliability performance.

Reliability Prediction	Stress Type	Stress
Internal Stress	Electrical	Voltage, Current, Power Dispatch
	Thermal	Heat
	Mechanical	Shock & Vibration Temperature Cycling
	Chemical	Water
External Stress	Weather	Temperature, Humidity, etc.
	Location	Pressure, Gravity, Radiation, etc.
	Maintenance	Operating Time, Practice Frequency
	Installation	Complexity

Table 2.2 Some Typical Stress Factors For Device Failure Prediction

Human Reliability Prediction	Performance Sharping Factors
Mental or Cognitive Effects	Competence Psychological Stress Education &Training Level Direct Field Experience
Environmental Effects	Human Interface Workload Weather Space Interruption & Recreation

Table 2.3 Some Typical Performance Sharping Factors For Error Prediction

The situational factors, on the other hand, are estimated by reliability experts based on their engineering judgement in order to consider the affect of these factors on reliability performance. Such estimation is subjective in nature and accordingly it is

Maintainability Prediction	Maintenance Conditions
Active Repair Time	Weather Confidence & Familiarity of Maintenance Detection Equipment Quality Test Equipment Quality Repairing Tools Availability of Spare Parts Complexity of Installation & Removal Availability of Maintenance Record & Device Manual
Administrative Time	Maintenancer Training , Rest Interruption & Recreation Stock Planning Level of Maintenance Transport Deployment Availability of Man Power

Table 2.4 Some Typical Maintenance Conditions For Maintenance Time Prediction

---

susceptible to human analyst influence. The situational factors are identified by both human experts' empirical knowledge and the correlation analysis, and are determined by comparison of their influences on the change of performance on a case by case base. The situational factors reflect the speciality of device or human reliability performance.

Numerous situational factors are identified in Military Standards (MIL-STD) and Military Handbook (MIL-HDBKS), as well as other text referenced in accordance with various devices and the underlying tasks. For a particular device or an operator and its task under analysis, it focus on only a certain number of factors by which the stronger influence imposes on reliability performance. Some of the commonly emerged factors which are induced through this work are listed in Table 2.2, 2.3, and 2.4.

3.5 System Reliability Combination

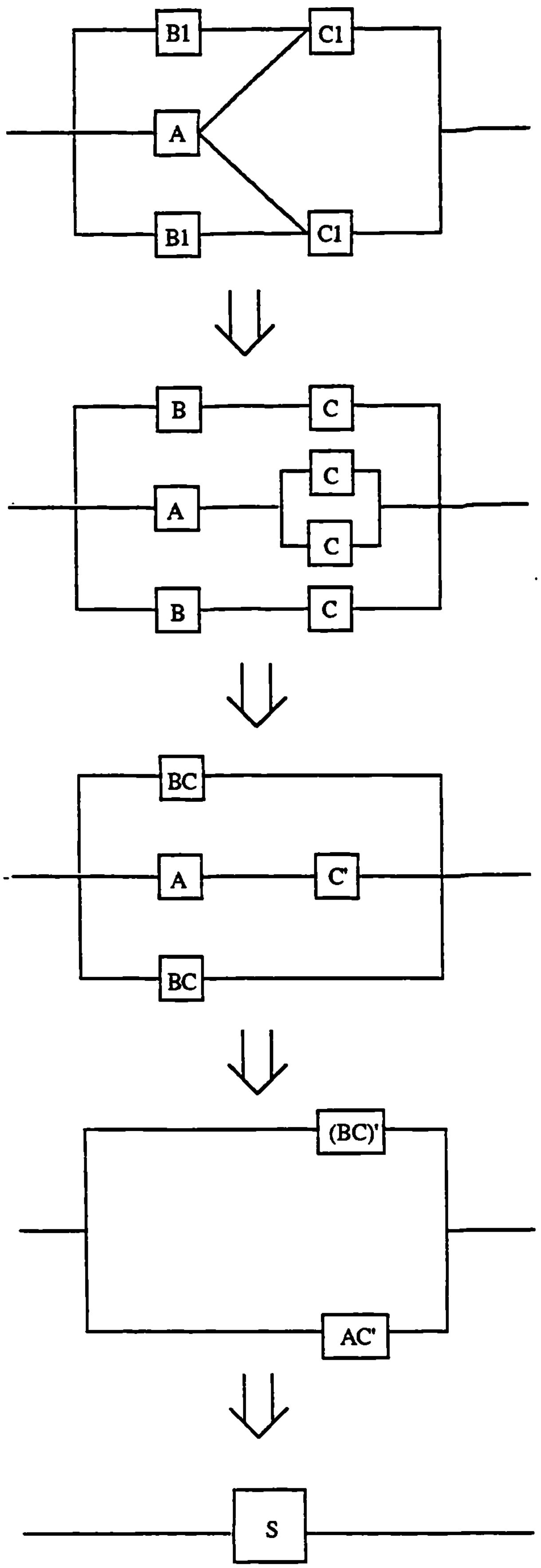
In general there are two major approaches to evaluate system reliability:- (1)analytical method, and (2) simulation method. In this thesis The former method is applied.

In the analytical approach, the method of system network diagram is widely used. System network is constructed by a set of blocks and arcs which represent devices and their links respectively. All device in a system network can be linked in a simple series form, a parallel form, or a complex series-parallel mixed form. Logically, a system network in series is that any device of the system failure will cause system failure. Respectively, A system network in parallel is that only if all device of the system failure will cause system failure. A simple series or parallel network is called the basic model. A basic model can be used to evaluate system reliability alone(e.g., system maintenance demand) , or forms an input to the complex model. A complex model is considered to be a series-parallel mixed network and its calculation is made using the results of the basic models as input.

The combination rules varies depending on whether two events are independent, mutually exclusive, complementary to each other, or one being a conditional event to another, which are stated in all probability text references[4,9,10,37]. Let's assume the events of failure and operating are mutually exclusive, and all device are independent, then for a series network model its reliability and failure probability can be calculated from

$$R_s = \prod_{i=1}^{n} R_i \qquad \text{eqn 2.15}$$

$$F_s = 1 - R_s \qquad \text{eqn 2.16}$$



$P_{B1}=P_{B2}=P_B$
$P_{C1}=P_{C2}=P_C$

$P_{C'}=2P_C-P_C^2$
$P_{BC}=P_BP_C$

$P_{(BC)'}=2P_BP_C-(P_BP_C)^2$
$P_{AC'}=P_A(2P_C-P_C^2)$

$P_S=P_A(2P_C-P_C^2)+$
$[2P_BP_C-(P_BP_C)^2][1-P_A(2P_C-P_C^2)]$

Figure 2.6 An Example of Calculating A Complex System Reliability

where R_i is the ith device reliability. Similarly, for a parallel system consists two devices with reliability R_A and R_B it can be integrated as

$$R_s = R_A + R_B - R_A \times R_B \qquad \text{eqn 2.17}$$

If there have more than two device in the parallel system then it is to have the remain device reliability integrated with the calculated reliability R_S using eqn 2.17 and repeat the process until all device are calculated. A complex model can be calculated by using eqn 2.15 and eqn 2.17 in turn wherever they are applicable.

To illustrate how a complex model is evaluated a sample system is presented in figure 2.6, which shows how a complex system reliability is calculated in a step by step manner. In this example the symbol P stands for reliability.

Briefly, a system reliability calculation normally encounter a complex series-parallel model. System maintenance is usually calculated as the product of each individual device maintainability. Human reliability is normally treated as a parallel event to a device reliability . Their product is the total reliability of a device.

2.6 Summary

In this chapter some of the fundamental concepts and techniques of device reliability prediction required in this thesis for further studying have been introduced and discussed.

The traditional probabilistic reliability prediction are divided into three sub prediction processes: device failure, maintenance time and human error. The concepts and procedures of each predictions are illustrated. It is believed that only if all three prediction are conducted then a complete reliability indication can be obtained. Particular interest is on the situational adjustment factors of reliability prediction which are identified and weighted based on human engineer's judgement. This awareness forms the backbone for further research which are presented in the later chapters. Finally, in this chapter a system reliability combination method is described and an example is given.

Chapter Three

Fuzzy Knowledge Based Device Reliability Prediction

3.1. Introduction

The discipline of reliability engineering encompasses a number of different activities, reliability estimation and prediction being the most important ones[7,37]. The conventional methods which are used very widely are based upon probability methods, where the probability of failure of a system is expressed in terms of the statistical information (probability of failure) of its sub-systems or components(see Chapter 2). However, in the situation that there has no such statistical information available, for examples, a newly invented device which has no service history, a core equipment for nuclear reactor which is too expensive to obtain its reliability data, or a part of space shuttle which is too difficult to obtain its reliability data to accomplish the task of reliability assessment, reliability engineers have to predict the basic reliability indices of these equipment subjectively through their experience or by comparison of the similar devices[2,5]. More often, even under the situation that the basic reliability index of a device is obtainable by laboratory test or through the sufficient operation record, because of the fact that the use conditions varies, these obtained objective information has no generality unless reliability engineers adjust it according to the actual working environment[4,7,37]. The adjustment made by engineer is based upon his judgmental knowledge which is subjective too. Those subjective information contains both randomness (refer to the frequency occurrence of the event) and fuzziness (refer to the compatibility of the prediction). As a matter of fact,

"It is recognised, however, that there is always some degree of subjectivity in reliability prediction. Consequently, it is not expected that accurate prediction can be made without the application of good judgement- prediction is still both an art and a science[4]."

A fuzzy reliability prediction framework is presented in this chapter. The term "reliability prediction" refers to the process of predicting individual device and operator reliability performance. The reliability performance are evaluated through the basic reliability indices such as failure possibility, maintenance time and human error possibility.

3.2. New Approach to Component Reliability Prediction

The probabilistic method is used in the reliability predictions. The device failure rate, Mean Time To Repair and human error rate are important concepts in device reliability. However, it is said that human judgement holds a central position in all reliability predictions of complex technical system according to the following facts:

(1) It is necessary to collect a large sample size of data to estimate the meaningful basic reliability indices. However, in practice, it is not likely that enough data can be collected to estimate these indices. Under the situation that the statistic data are either unavailable or incomplete the basic reliability indices have to be estimated by experts based on their engineering judgement.

(2) Device reliability, maintainability and human reliability are affected by many factors, e.g., the environment in which devices is operated and repaired, the environmental task condition, psychological stress of a human operator, etc. In the conventional reliability predictions the basic failure rate, Mean Time To Repair and human error rate are adjusted by experts based on their engineering judgement in order to consider the effect of many factors on reliability.

In traditional approach to reliability predictions, human experts' judgements are expressed quantitatively as either a subjective probability singleton, or a confidence interval. Such expression has been criticised by the facts which were discussed in Chapter One. The arguments are based on the fact that the inherent uncertainty in human experts' judgement is fuzziness in nature rather than randomness. To clearly illustrate it, consider a imaginary dialogue which simulate a session of completing reliability work sheets by a reliability expert:

Query:	What is the name of the system?
Reliability Expert:	British Nuclear Merseyside Plant.
Query:	What is the name of the device under analysis?
Reliability Experts:	Reactor ALPHA.
Query:	Is reactor ALPHA at the lowest hardware level?
Reliability Expert:	Yes.
Query:	Does reactor ALPHA fail to sever power often?
Reliability Expert:	There has no sufficient test record for this new device. However, by comparison with other similar reactors, the frequency of a failure per year is <u>about 5</u>, it could only be 3, sometimes even 8 failures per year might occur.
Query:	Is the environmental condition, for example, the operation room temperature has significant influence on the failure of reactor Alpha? If so, what is the extent of such effect?
Reliability Expert:	Yes. In general if the temperature is <u>very high</u> then reactor Alpha fails <u>more frequently</u>.
Query:	Is the weather condition contribute significantly to the maintenance time of reactor Alpha? If so, what is the likely relationship between them?
Reliability Expert:	Yes. If the weather is extremely <u>cold</u> or <u>hot</u> then the preparation time for maintenance is <u>much longer</u>.
Query:	Do human operators play important role in reliability of reactor Alpha?
Reliability Expert:	Yes, very much. The <u>more competent</u> the operators are, the <u>less chance</u> the reactor fails.

From the above hypothetical dialogue, there are four observations: 1) There are various kinds of domain knowledge existing such as cause-effect relations between reliability performances and the situational facts affecting reliability performance, the extent of such affecting etc.. 2) The relation between reliability performance and the situational factors is not a necessary and sufficient one. So it is difficult to express this kind of relation precisely in terms of quantitative mathematics. 3) Knowledge of reliability performance is comparatively easy to be expressed in the form of natural language with which the human is usually associated. 4) Human experts express their knowledge in a very imprecise way as is reflected by the natural language expression. These observations have, in fact, formed a backbone of the fuzzy knowledge structure (rules) in this chapter which is based upon human judgmental and experiential knowledge.

Although there are many proposed approaches of applying fuzzy concepts to the reliability analysis, to the author's knowledge, Onisawa is the only one who emphasises the necessity of applying fuzzy concepts to modelling relationship between reliability performance and its affecting factors[70]. Being aware of the fact that such relation largely be concluded by human experts based on their experiences, and the fact that such experiences are comparatively easy to be expressed qualitatively rather than quantitatively, he proposed in his model that the qualitative relation between reliability and affecting factors can be expressed in the form of a set of rules. Three typical factors are considered in determining device reliability, namely the environmental condition; quality of maintenance and the device working time. Fuzzy terms like 'good', 'bad', 'high', 'low' are contained in rules in the form of 'if the quality of maintenance is good, then the device reliability is high'. Such fuzzy terms are then defined in a likelihood space within the interval of [0, 1]. It assumes that human expert's estimation is usually expressed in the form of a triplet $[\lambda_L, \lambda_M, \lambda_U]$ where λ_M is the recommended value of failure rate, λ_L is its lower bound and λ_U is its upper bound. A subjective given membership function is defined in which the estimated rate and its bounds are treated as the parameters. By mapping from probability space to likelihood space fuzzy concepts like " Failure Possibility" and "Error Possibility" are introduced in. Such mapping is defined in accordance with possibility and probability consistence principle, which implies that even if the rate is estimated to be very small from the viewpoint of probability reliability, there is a high possibility that device breaks down. The computation of system failure possibility are based on fuzzy T-norm and T-conorm operators as illustrated " AND" and "OR" gate.

By reviewing Onisawa's work, it is discovered that apart from his pioneering contribution of introducing fuzzy concepts into reliability analysis, there are still many issues which need to be further explored, such issues are-: (1) A detailed, systematic work is necessary t to fully explore the relations between reliability performance and many associated situational factors. The exploration should be conducted not only device reliability but also human reliability as they make a complete reliability prediction process. (2) A fuzzy linguistic reliability prediction framework is necessary to be developed. Such fuzzy model should be able to accommodate the inherent uncertainty associated in human experts' knowledge expression and gives maximum flexibility for such expressions. (3) A formal reasoning strategy should be developed to process imprecise knowledge from "root source" data to decision level. It have been proved that the only appropriate tool for this purpose is the possibility theory based fuzzy approximate reasoning[96,98].

Nevertheless, Onisawa's pioneer work has motivated the author to develop a fuzzy rule based framework for reliability predictions. Such framework can be illustrated graphically in Figure 3.1., and is presented in the following sections. In a broad sense, reliability prediction should include the system integration process. However, in this thesis the term of "reliability prediction" is defined to refer to the process of individual device(which is at the lowest hardware level) reliability index prediction only . The process of computation of fuzzy reliability information in order to analyse system performance is presented in the next chapter.

3.3. Fuzzy Sets Theory and Fuzzy Reasoning Based Reliability Prediction

The building of a fuzzy rule based reliability predictions framework would have to accommodate a variety of uncertainties illustrated in the above section. The first type of uncertainty namely " imprecision" is related to the inaccuracy of empirical results and the subjectivity of certain judgement. Fuzzy terms in the statement of the hypothetical dialogue such as " roughly around", " extremely cold" and " much longer" are ill defined. This type of impression is associated with the degree---how extremely cold is -5^{o} C of temperature? There is no clear boundary for a definition which is imprecise and fuzzy in nature like " extremely

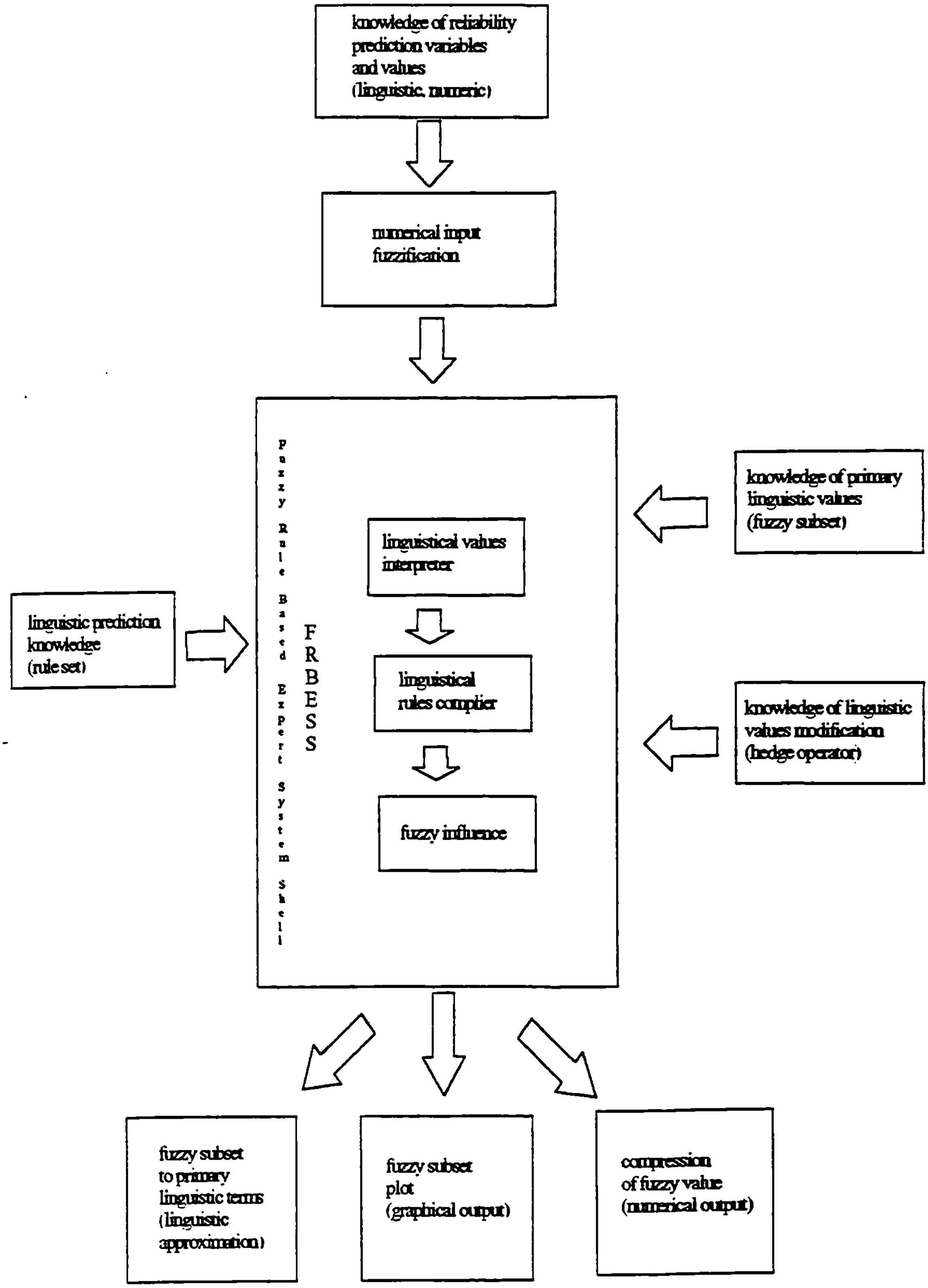


Figure 3.1 Outline of the Modules of the New Proposed Approach

cold", but nevertheless such linguistic quantities are personally meaningful and are important for decision makers. The second type of uncertainty namely " vagueness " is in relate to the human problem solving strategies, i.e., the concepts used and the cause-effect relationship expressed. Human beings when making decisions tend to work with imprecise concepts (as indicated in section 3.2) which can often be expressed linguistically. According to Zadeh[94]

" *For many purpose, a very approximate characterisation of a collection of data is sufficient because most of the basic tasks performed by humans do not require a high degree of precision in their execution. The human brain takes advantage of this tolerance for imprecision by encoding the 'task-relevant' information into labels of fuzzy sets which bear an approximation relation to the primary data*"

Similarly, the way in which a reliability engineer expresses a judgement on reliability performance is likely to be as a rather vague relationship, using ill defined linguistic quantities such as STRONG, NORMAL, HIGH, etc. A typical example might be

IF the comparative influence of the internal stress is *positive strong*
AND the comparative influence of the external stress is *negative weak*
AND the basic failure estimation is *low but not too low*
THEN the chance of device failure is *more or less moderate*

3.3.1. Fuzzy Sets As A Representative Tool For Imprecise Knowledge

In brief, there exists a need to represent " imprecision" and "vagueness" in an integrated way. For instance, extremely cold weather significantly influence the chance of device failure. Hence, this implies that there is an interaction between these two types of uncertainties.

In this section, some of the basic concepts of fuzzy sets theory (FST) are introduced and are illustrated with examples. It is shown how fuzzy sets can be used to represent such imprecise concepts as "high", "strong" etc. these are notions that have an important intuitive meaning, but which are difficult to represent in a precise, mathematical way.

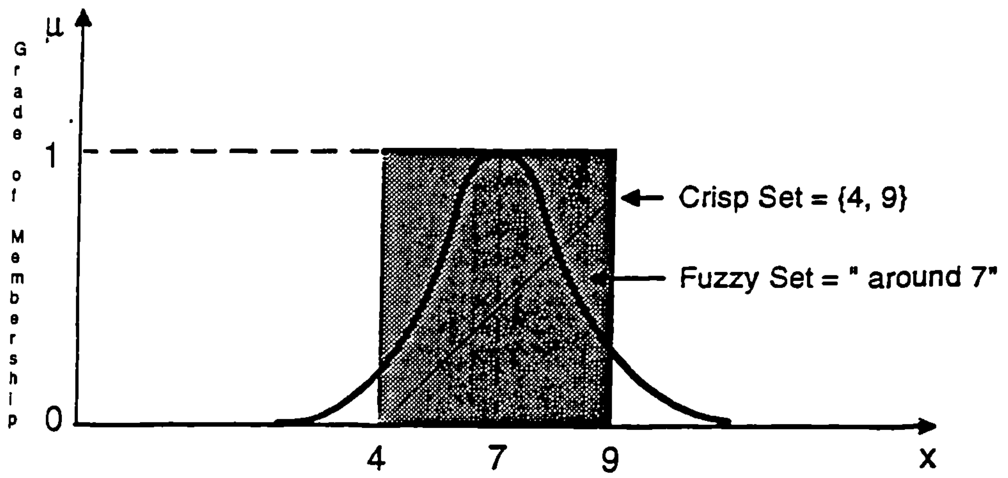


Figure 3.2 Crisp Set and Fuzzy Set

In classical Boolean logic, sets consist of a collection of elements which may be grouped together. An object is either an element of the set or it is not. The characteristic function of the set can take the values 0 or 1. to represent the element's grade of membership in the set. This is the usual definition of a set. To distinguish the traditional kind of sets from fuzzy sets, they will be referred to as crisp sets as illustrated in Figure 3.2. The operation which can be applied to crisp sets are familiar union, intersection and complement. These sets can be used to represent classes of objects where there is a well defined boundary between members of the set and non members. In Figure 3.2, an example of the set of numbers which lie between 4 and 9 are shown. This set is well defined , in that any number is a member if it is between 4 and 9. The characteristic function of this set will take values 0 and 1.

However, not all classes are so well defined. For example, a set like " between 4 and 9" one would have no hesitation in placing number 5, 8 within this set. But what about number 5, 8 for a set like " around 7"? They are likely to be found within the set, but whether they can be strictly classified as members of the set is not so easy to decide. In this case, " around 7" can be defined as a fuzzy set to group these numbers, and assign each number a grade of membership which lies somewhere in the interval 0 to 1. The actual value of the grade of membership is chosen by the person who defines the set and represent that individual's understanding of the meaning of the set. Fuzzy sets are not crisp in nature as illustrated in Figure 3.2 where a fuzzy set describe the set numbers that are " around 7". The symbol μ is used to denote grade of membership.

3.3.2. The Use of Linguistic Description in Reliability Prediction

In order to permit the manipulation of fuzzy concepts to represent vague reliability prediction rules, " linguistic variables" are required to represent the predicting variables. A linguistic variables is a fuzzy variable whose value in any one particular instance is a fuzzy subset of a universe of discourse coded by linguistic descriptions[3].

The overall reliability prediction is obtained in a traditional approach as the product of basic estimation, (i.e. failure rate, maintenance time and human error rate) and a set of the associated situational factors. The basic estimation can be either a numerical value or a linguistic value, depending on the source of information obtained. An assignment of values to the situational factors is subjective by the nature of human judgmental and experiential knowledge. Such assignment in a traditional approach is in the form of a crisp numerical value which is obtained by comparing reliability performance before and after a situational factor applied. It can be expressed mathematically as

$$\text{Value of a situational factor} = \frac{\text{reliability performance after a situational factor applied}}{\text{reliability performance under the normal condition}} \qquad \text{eqn 3.1}$$

The above equation can be interpreted as the degree of the comparative influence of a situation factor applied on reliability performance. Thus, the numerical variable " comparative influence" defined as F whose universe of discourse range in $0 < F < \infty$ in theory is the base variable for the situational factors. For the convenience of linguistic vocabulary, the universe of discourse of this variable can be extended to $-\infty < F < \infty$ by a logarithm transfer formula (see eqn 3.3). A linguistic value such as " positive strong" therefore can be defined and interpreted as a label for the fuzzy restriction which characterised by its grade of membership (compatibility) function on the points of the universe of discourse, namely "the comparative influence".

The basic estimation, on the other hand, can be derived either by statistic method or by human judgmental knowledge. According to Karwowski, even an event " failure" is clearly stated, and the concept of probability as suitable for reliability prediction is well defined, it does not provide for the sharp probability estimates needed to generate adequate reliability estimation. Instead, the quantification of " chance of failure" is imprecise since it uses linguistic descriptions like: extremely high, moderate, more or less low, etc. Karwowski argued that in the causes where human judgement and adjustment are essential, the assignment of probability is vaguely defined. Based on such fact a linguistic variable " Possibility of Failure" is defined for device reliability prediction with the typical fuzzy labels, such as : high, moderate, low etc., and with the understanding that " possibility of failure" is synonymous with a familiar frequency measure " failure rate". Linguistic variables and its fuzzy labels for maintenance time prediction can be also defined with the understanding that the linguistic variable for basic estimation shall be synonymous to a time measure.

It is emphasised by Feagons [27] ,that although the meaning of the proposed linguistic values are open to individual interpretation, the differences in subjective assessments can be resolved by extending the precision of associated verbal definitions through discussion among the experts in the field of reliability analysis. It is very important that the structure of verbal descriptions does not cause misunderstanding, and this can be prevented if the agreed upon definitions are provided. As indicated by Cooley and Hicks [17] , primary linguistic values should have an intuitive appeal and be easily differentiated. For this reason, A sets of linguistic prediction variables and their labelled primary linguistic values are proposed in table 3.1 for device failure possibility , maintenance time, human error possibility predictions respectively. Based on these defined variables and values a prediction rule for device maintenance time in the natural language form may be defined as

IF the comparative influence of the variance of active maintenance time is *normal* AND the comparative influence of the variance of maintenance administrative time is *positive strong* AND the basic estimation of the maintenance time is *more or less long*

THEN the total device maintenance time is *much long*

Primary Linguistic Value	Fuzzy Reliability Predictions Variable
Lowest, Low, Between_low_and_moderate, Moderate, Between_moderate_and_high, High, Highest	Failure Possibility
Shortest, Short, Between_short_and_medium, Medium, Between_medium_and_long, Long, Longest	Maintenance Time
Positive_strong, Positive_weak, Normal, Nagative_weak, Nagative_strong	The Comparative Influence Of A Situational Factor

Table 3.1 Fuzzy Linguistic Reliability Prediction Variables and Their Labels

3.3.3. Interpretation of the Linguistic Values

The foundation of linguistic definition using fuzzy sets theory consists of three basic concepts -: fuzzy variables, primary linguistic values and modification rules. In order to develop the primary linguistic values for fuzzy reliability prediction variables, a degree of membership or possibly rating is assigned to each possible value of a linguistic (prediction) variable. The assignment of linguistic values is based on the canonical form of S and P function defined by Zadeh [97], as

$$
\begin{array}{lll}
S(X;a,b,c) & = 0 & x \le a \\
 & = 2[(x-a)/(c-a)]^2 & a \le x \le b \\
 & = 1-2[(x-c)/(c-a)]^2 & b \le x \le c \\
 & = 1 & x \ge c \\
P(X;b,c) & = S(X;c-b,c-b/2,c) & x \le c \\
 & = 1-S(X;c,c+b/2,c+b) & x \ge c
\end{array}
\quad \text{eqn 3.2}
$$

where X is the base value

a is X at which $S = 0$

b is X at which $S = 0.5$

c is X at which $S = 1$

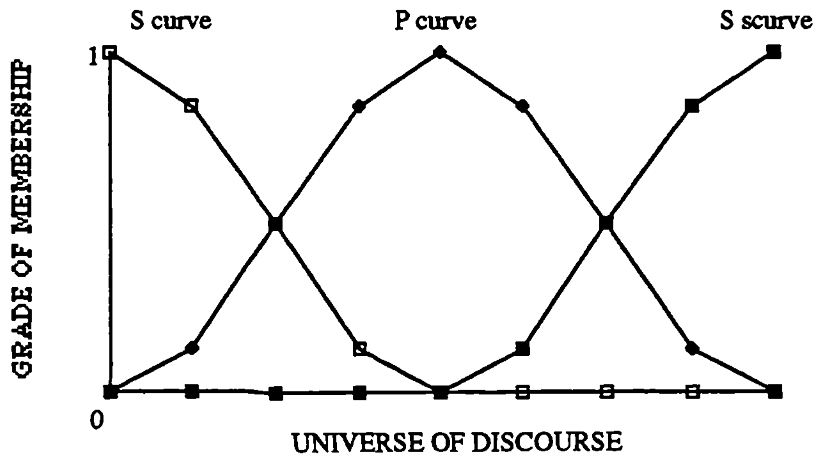


Figure 3.3 S and P type Fuzzy Number

The above type of fuzzy numbers are illustrated in figure 3.3. In choosing the linguistic variable X for reliability predictions, the following guidelines were taken into consideration [20]-:((1) The variable should accurately reflect the meaning of the linguistic value; (2) The values associated with a particular linguistic variable should not change because of low or moderate uncertainties, (3) Strong judgement changes should be recognised by the appropriate movements along the universe of discourse, and (4) Small changes in judgement should not significantly affect the results of the model. In reliability prediction. the scales of the universe of discourse of the situational factors and the basic estimation values vary significantly in accordance with the different type of devices. Furthermore, even for the same type of device the scales can be too broad to define a set of sensible linguistic values on it. For the sake of simplicity, such difficulties can be greatly reduced by the following methods: (1) divide devices into several categories in which all devices shall possess similar characteristics, e.g., electronic devices. Thus, the interested universe of discourse can be bound into a manageable scale, and a limit number of linguistic values can be sensibly defined on such scale. For example, the values of the situational factor for electronic devices range from 0.1 to 10 in most cases [1, 2]. (2) the points of a universe of discourse can be converted by a properly defined transition formula, so that a set of more meaningful linguistic values can be defined on a new universe of discourse. In reliability predictions, such transition formula might be defined in the form of

$$f(x) = a \log(x) + b \qquad \text{eqn 3.3}$$

where x is a variable on the original universe of discourse

a , b are parameters

f(x) is a variable on the new universe of discourse

Thus if let a=2.5 and b=0, the range of a universe of discourse " the comparative influence of x stress" is transited from [0.1, 10] to [-5 , 5]. A linguistic value "positive strong" defined on the new universe of discourse is more appropriate and meaningful. (3) to simplify computation a continuous variable normally be discrete so that fuzzy computation can easily apply on to a limit number of values. In general, a set of discrete numbers can be divided into a few categories . Each categories has a fuzzy label (linguist value). For example, a continuous variable "the comparative influence of x stress " in [-5 , 5] can be divided into 5 categories, namely PS, PW, NO, NW, NS. The grade of memberships for the chosen linguistic values are represented by a string of numbers rather than a continuous function. In the computerised version of the proposed systems, the users are able to derive the representations of the primary linguistic values by using the canonical of the S and P functions (eqn 3.2), and adjusting the appropriate parameters. It must be emphasised that the definitions of the most important linguistic values are empirical and the satisfactory result by applying such pre-defined linguistic values are largely depended on assessor's experiences. It also need to point out that the assessor himself is a essential source of fuzziness, since the same fault event may be perceived differently depending upon the individual experience and preferences in reliability analysis.

Once the universe of discourse and the primary linguistic values of a fuzzy variable are determined, other linguistic values can be derived from the primary linguistic values by using the modification rules. The modification rules are a set of pre-defined fuzzy operations which are normally called " linguistic hedges". A linguistic hedge is defined in the way that it is a fuzzy subset of the primary linguistic term. There are two basic types of linguistic hedges, using the shift operator and the power operator. A power operator, such as " very " will changes the shape of the primary fuzzy linguistic term like "positive strong". If " very " is represented by a power operator :

$$\mu_{\text{very PS}}(x) = \mu_{PS}^{2}(x) \qquad \text{eqn 3.4}$$

This definition ensures that the grade of membership of an individual in the set " very PS " is less than the grade of membership in the set " PS ". Thus " very PS " is a subset of " PS ". This seems sensible enough. (see figure 3.4). However, the problem with power operator is that the grade of membership for " PS" and " very PS" reach the grade 0 and 1 at the same points. This might be satisfactory for some applications, but in other cases it is preferable to use a shift operator such as :

$$\mu_{\text{great than PS}}(x) = \mu_{PS}(x - c) \qquad \text{eqn 3.5}$$

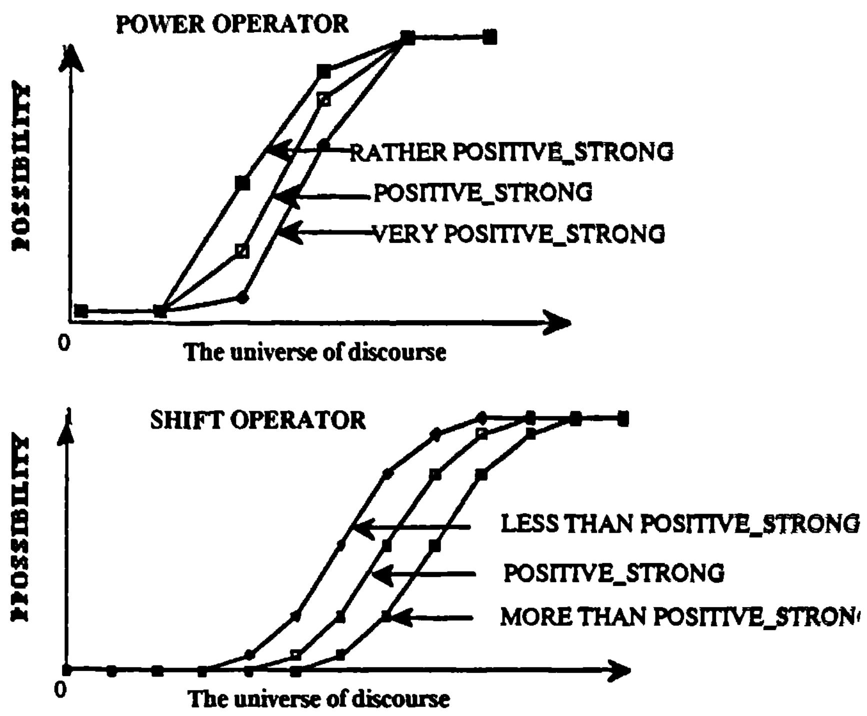


Figure 3.4 Shift and Power Linguistic Hedge

Shift operators do not affect the shape of the fuzzy set in the way that power operators do. they merely shift it along the axis. Both operators satisfy the subset identity; ensuring for example that " very PS " is a subset of " positive strong " :

$$\mu^2_{\text{positive strong}}(x) \le \mu_{\text{positive strong}}(x)$$
$$\mu_{\text{positive strong}}(x - c) \le \mu_{\text{positive strong}}(x) \qquad \text{eqn 3.6}$$

Hedges like " very " , " rather " , " great than " and " less than " on the primary term " positive strong " are illustrated in figure 3.4. Words and phrases such as "more or less", "much ", " fairly " , and "extremely " etc. are also defined as hedges in fuzzy sets theory. These Hedge operators can be combined to produce more complex expressions such as " positive weak but not too weak " (see Appendix I). By using hedges it offers great power for representing meaning.

3.4. Constructing Fuzzy Relations of Prediction Variables

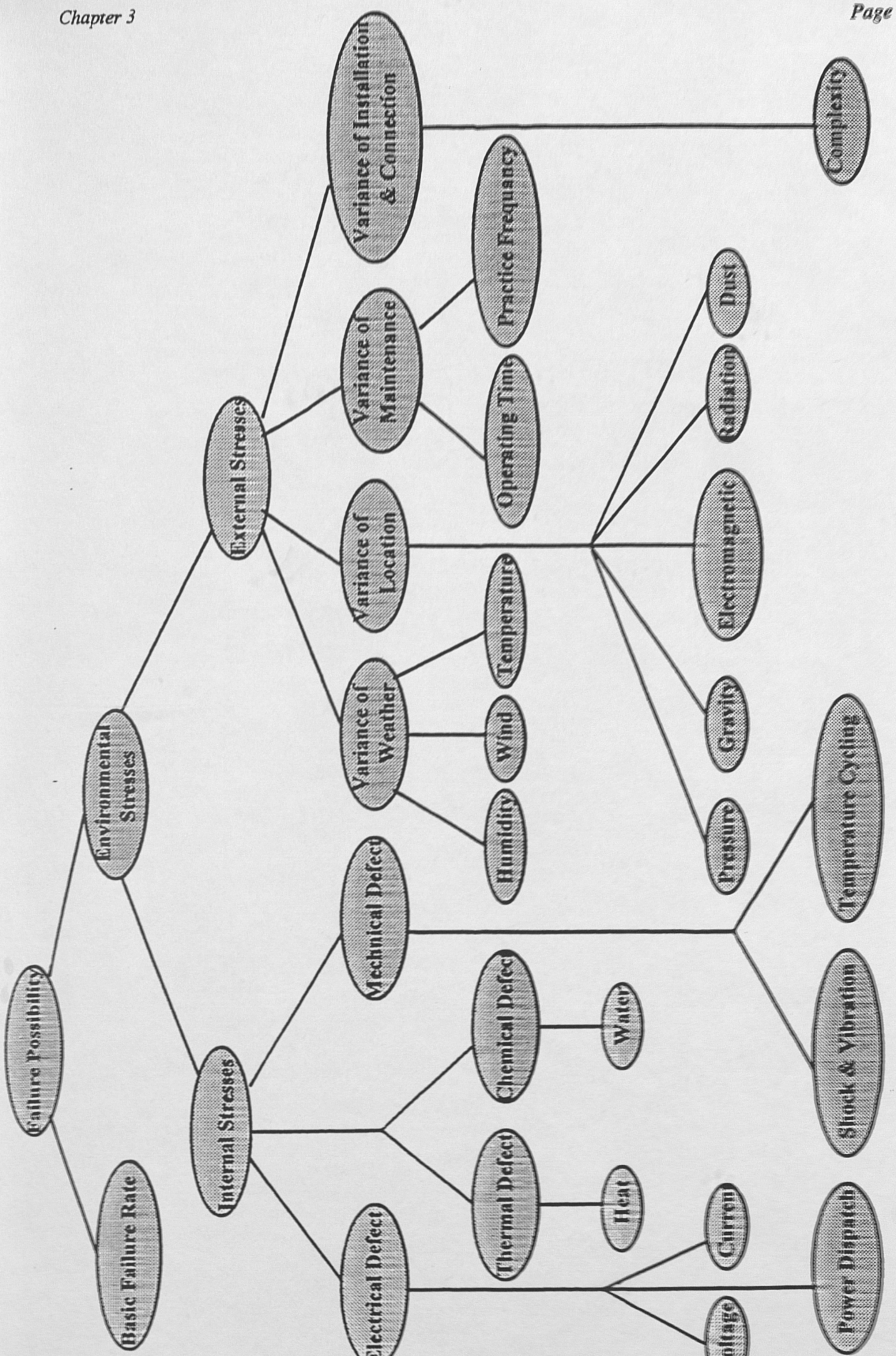
Instead of establishing the functional relationship for non-fuzzy variables in conventional problem analysis, fuzzy logical relations are essential to be constructed in all fuzzy models where fuzziness is seen as an attribute. The construction of such logical relations is based upon-: (1) a knowledge tree which is represented in a logical form of relating one decision variable to the others, and (2) a set of fuzzy connective operators. (3) a selected fuzzy implication function.

3.4.1. Reliability Prediction Knowledge Trees

To predict reliability performance under a fuzzy environment, the domain knowledge of device and operator state, the situational factors etc must be organised in a logical manner such as to arrange the knowledge into a knowledge tree. Three typical knowledge trees for predicting generalised device failure possibility, maintenance time and human error possibility are illustrated in Figure 3.5, 3.6, and 3.7 respectively. These knowledge trees represent the domain knowledge of reliability prediction, such as the knowledge of-: (1) concepts and relations, (2) facts and heuristics, (3) policy and procedures. They are mainly deducted from the relevant literature [2,4,7,14,37,50,70] throughout this study. However, in real applications the type of knowledge has to be identified so that proper elicitation of knowledge tree can be carried out. The process of knowledge elicitation is the so called "knowledge pruning" in Knowledge Engineering (KE). The problem solving process is then by pruning through the knowledge tree to select and establish the correct path from the "root variable" (e.g. reliability source information) toward the "target variable" (e.g. prediction goal) of the knowledge tree.

3.4.2. Fuzzy Relational Metrics Construction

Knowledge tree is normally represented in the form of a group sets of "IF-THEN "rules. The rules in each knowledge source can be quite complex in form with nested IF statements, antecedents linked together by AND or OR connectors, consequence which recommend decision as well as suggesting other IF conditions etc. However, rule acquired in



<u>**Figure 3.5 Knowledge Tree Of Device Failure Possibility Prediction**</u>

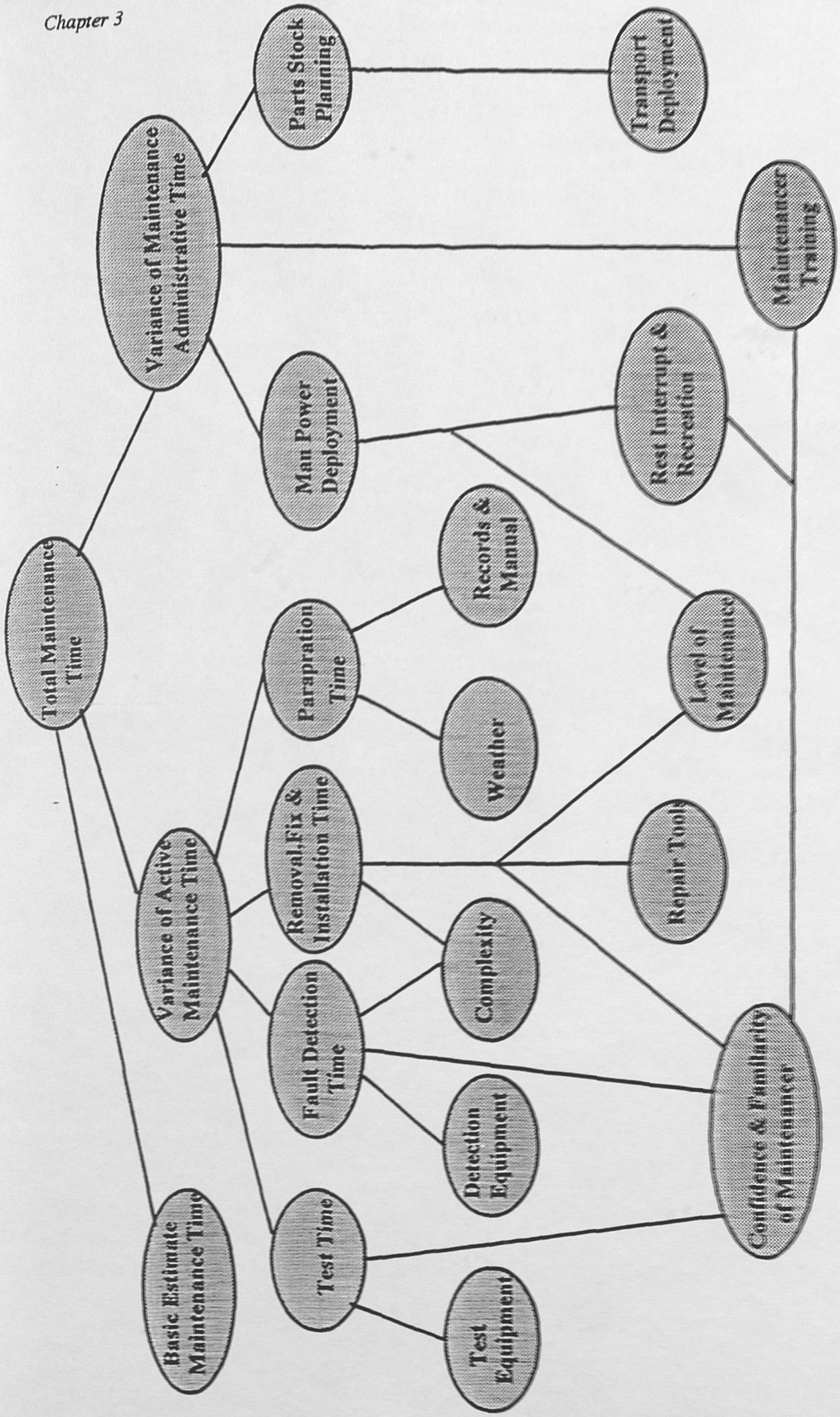
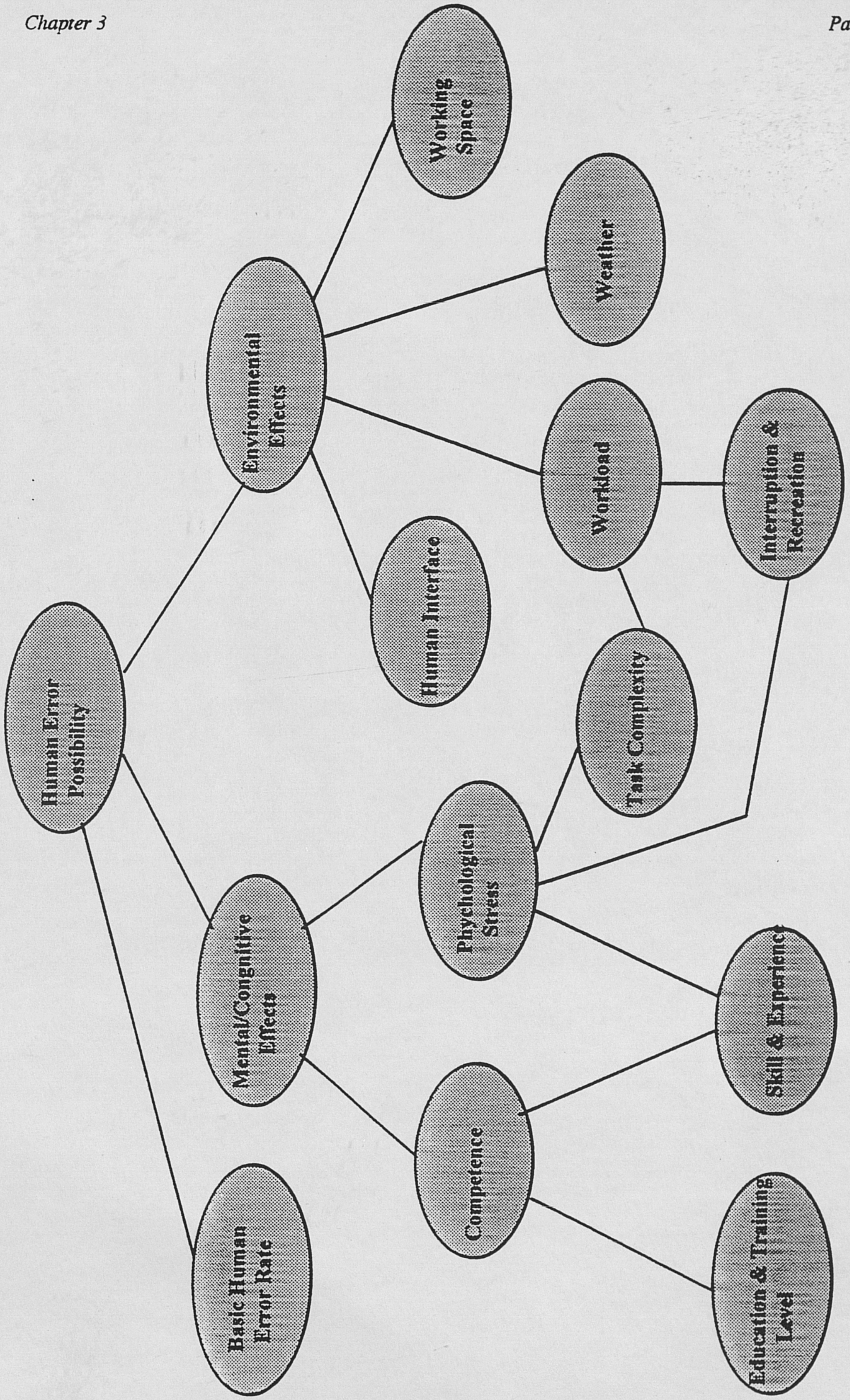


Figure 3.6 Knowledge Tree Of Device Total Maintenance Time Prediction



<u>Figure 3.7 Knowledge Tree Of Human Operator Error Possibility Prediction</u>

this thesis have been chosen to have a classical "IF-THEN" structure to reduce the representation complexity (see Appendix III).

Each branch of a decision tree constructs a ruleset. A branch node represents a rule consequent premise. The leave which is connected to this node represents an antecedent. An antecedent leave can be a consequent branch node for another ruleset if it has leave beneath it. Thus, the number of rulesets is the number of branch node in a decision tree.

A ruleset consists rules which have same linguistic variables but different values in order to present all possible situations. For illustration, a rule in a ruleset which is a fuzzy conditional assignment of a device reliability prediction situation is described as (IF X is A [condition] THEN Y is B[consequent]), where X is an antecedent condition representing the degree of comparative influence of a situational factor on device reliability performance, and Y is the consequence of the degree of degradation of device reliability performance, respectively. To represent the relationship between the objects of X and Y is to translate them into a conditional possibility distribution of fuzzy relation R where

$$\mu_R(x,y) = \mu_{X\to Y}(x,y) = I\{\mu_X(x),\mu_Y(y),x \in X,y \in Y\} \qquad \text{eqn 3.7}$$

A fuzzy relation R is simply a fuzzy set defined in a Cartesian product space ($X \times Y$) or effectively R is fuzzy matrix of X and Y. To construct R, a fuzzy implication operator I must be assigned, where R is characterised by a multi-values membership function $\mu_R(x,y)$ and is expressed by

$$\mu_R(x,y) = I(\mu_X,\mu_Y) \qquad \text{eqn 3.8}$$

Implication operator I can be interpreted here as a combination operator to be determined for conditional possibility statement, namely

Possibility (x=a and y=b)= Possibility (y=b given x=a) *I* Possibility (x=a) eqn 3.9

Many implication operators have been suggested since the generalised modus ponens initially stated by Zadeh [55]. However, The choice of fuzzy implication operators remains critical in any fuzzy reasoning based decision systems, for it directly influences on the fuzzy reasoning performance. In another word, the success of applying fuzzy reasoning to any decision systems largely depends on how to select an appropriate implication operator. A discussion and comparison of some typical fuzzy implication operators toward the design of Fuzzy Rule Based Expert System Shell (FRBESS) is described in Chapter 6.

3.5. Fuzzy Reasoning Based Reliability Predictions

Mathematically, three properties of fuzzy sets are required for fuzzy reasoning: (1) Implication function (2) Aggregation of rules (3) Inference mechanism. The rules of fuzzy inference are based, in the main, on two principles: (a) entailment principle, and (b)translation principle [64] .The translation principle deals with the translation of a fuzzy variable to its possibility distribution. The entailment principle consists of two concepts:- conjunction rule and projection rule. On combining these two rules (usually conjunction followed by projection), Compositional Rule of Inference (CRI)[62] is obtained which constitutes the foundation of human reasoning.

3.5.1. The Outline of Fuzzy Reasoning

Informally, Fuzzy Reasoning (FR) is the process by which a possible impreci conclusion is deduced from a collection of imprecise premise. Hence, the nature of FR is regarded as approximate ratter than exact and also semantic rather than syntactic. Several different approaches of fuzzy reasoning have emerged as stated in Dubois and Prade's review paper [22]. Accordingly to Dubois *et al* there are two alternative but equivalent approaches of fuzzy reasoning: fuzzy logic based truth value restriction reasoning and possibility theory based multi-values compositional rule of inference. However, it has appeared that the former approach has less attraction due to its philosophical drawbacks though it has a favourable computational aspect than the later approach. This thesis follows the current research trend in fuzzy reasoning and concentrates on Zadeh's approach using the compositional rule of inference technique.

Once the implication operator was determined, fuzzy relation, or the so called "fuzzy matrix" for it is represented by a matrix form, of a rule can be constructed based on the selected implication function (eqn 3.8). The next task to proceed fuzzy reasoning is to aggregate all rules in a ruleset to form a single rule in terms of combining each fuzzy matrix of a rule into a ruleset matrix. In differ to the ordinary "IF-THEN" production system of which the deduction process is to select the rules which are triggered, fuzzy "IF-THEN" rule system is working on a "partial matching" methodology by which all rules must be encountered for their impact. Aggregation of all rules in a ruleset is to simplify reasoning process. Such process normally invokes disjunction operation(MAX) to make sure that all rules are considered will likely have an effect. Hence, for N rules in a rulest, each individual fuzzy relational matrix is aggregated to form an overall R of the ruleset

$$R = \mathop{\circ}_{i=1}^{N} R_i \qquad \text{eqn 3.10}$$

where o donates the operator MAX. The composite rule, after aggregation process, can be translated from contour plot to numbers by dividing it up into a finite number of squares and finding the maximum grade of membership in the square. This will only be an approximation, but it is usually adequate. Let it still be an abstract rule (IF X is A THEN Y is B), denote the input set by A, and the composite rule which relates the linguistic variables of input and output (or antecedent and consequent) by R, to find the consequence B of Y due to X can be inferred by the composition of A and R which can be expressed as:

$$\begin{aligned} &\Pi x \rightarrow A\,(\text{input data}) \\ &\Pi(y/x) \rightarrow R\,[R_{A\rightarrow B} = \{\mu_R(x,y)/(x,y)\}] \\ &\Pi y \text{ is } \Pi x \circ R \Rightarrow \mu_y = MAX(MIN(\mu_R \mu_x)) \end{aligned} \qquad \text{eqn 3.11}$$

where 'o' is the composition of fuzzy relations and $(\mu_R \mu_x \mu_y)$ are the membership functions of R, X and Y. A typical fuzzy inference sequence with two fuzzy rules is shown in Figure 3.8. The compositional Rule of Inference has many remarkable mathematical properties. Reasoning both forwards and backwards can be accomplished. Reasoning forward is the case where both A and R are known and it is to find the consequence B. On the contrary, reasoning backwards is the case where B and R are known and it is to seek the set of possible input A which could have caused a particular output B. In the case of reliability predictions it is natural to adopt forward reasoning.

3.5.2 Reliability Prediction Using FR

The situational factors were identified; the basic estimations were classified; and the knowledge trees were established. What remains to do is to deduct the information at decision level, which are approximate but adequate, of Device Failure Possibility, Device Total Maintenance Time, and Human Error Possibility. Such process will accomplish a complete reliability prediction task in a generalised meaning. Fuzzy compositional rule of inference is utilised for this purpose.

The following example is aimed to indicate how CRI is applied to device reliability prediction. Suppose that due to the effect of both external stress and internal stress, e.g. the influence of over heat, strong humidity etc., significant impact on device reliability performance (degradation) may occur which will leads to the event of device failure. The possibility of device failure is subjected to a number of factors such as random failure within the designed expectation (represented in the basic failure estimation). For the sake of simplicity, it is assumed that the device failure is only due to the fact of environmental stress. Using the expressive capability of fuzzy reasoning, the fuzziness of the above situation can be linguistically synthesised as an IF-THEN condition:

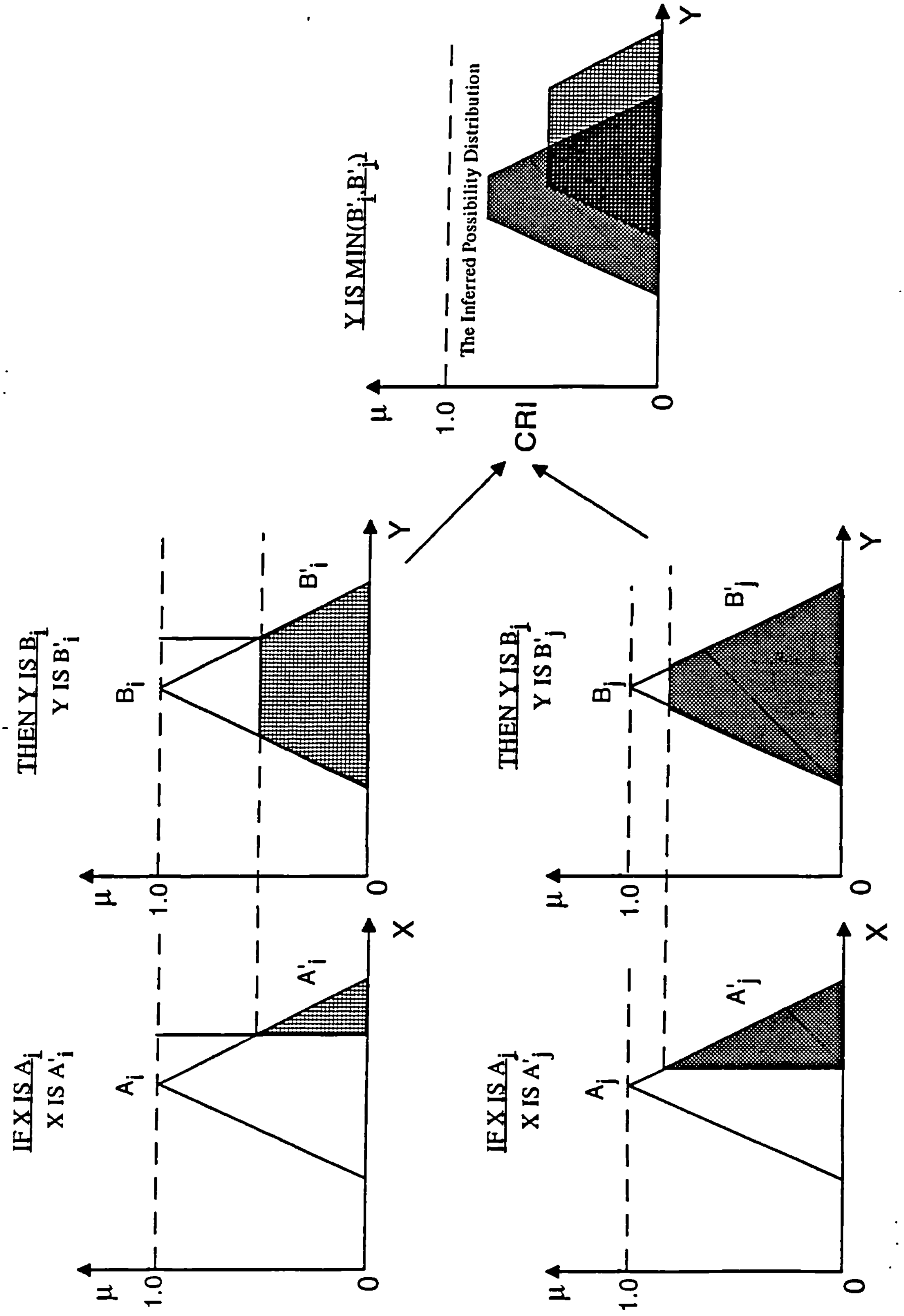


Figure 3.8 A Typical Inference Sequence With Two Fuzzy Rules

*IF the comparative influence of environmental stress is **positive strong***

*THEN the device failure possibility is **high***

The above rule can be translated into an abstract form as

IF X is PS THEN Y is HI

where X be the antecedent condition representing the comparative influence of an environmental stress on a device reliability and Y be the consequence deduction of the possibility of a device failure. If the universe discourse of X and Y are defined as the discrete sets in the range of :

$X \in [-5,5]; Y \in [0,10]$

and the linguistic terms set for each linguistic variable are:

X-{nagetive_strong(NS), nagetive_weak(NW), normal(NO), positive_weak(PW), positive_strong (PS)}

Y-{lowest(LT), low(LO), between_low_and_moderate(BLAM), moderate(MO), between_moderate_and_high(BMAH), high (HI), highest(HT)}

Then X and Y can be translated into possibility distributions by using S and P fuzzy numbers if we define PS and HI as

X		Y
$\mu_{PS}(x) = S(x{:}2,3.5,5)$	;	$\mu_{HI}(y) = S(y{:}7,8,10)$

$$Poss(x) := \prod_{PS} = [0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.22,0.78,1.0]$$
$$Poss(y) := \prod_{HI} = [0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.50,0.78,1.0]$$

A two dimension implication matrix $R_{A \to B}$ between X and Y would result by using Mamdani's implication operator (i.e., $A \to B = \min(a_i, b_j)$)

reliability cause a "high" possibility of device failure can be inferred through the above procedures.

In addition to the device reliability prediction, device maintenance time and human error possibility can also be inferred using CRI. Suppose the variance of the preparation time has a significant influence on the length of active maintenance time. The conditional statement might be described as

IF the comparative influence of the preparation is ***positive weak***

THEN the variance of active maintenance time is ***more or less normal***

or If X is PW Then Y is more_or_less (NO). PW and NO are defined as P type fuzzy number and fuzzy hedge "more_or_less" is defined as

$$\mu_{more\_or\_less}(x) = \mu(x)^{0.5} \qquad \text{eqn 3.12}$$

Hence,

$Poss(x) := \Pi_{PW} = [0,0,0,0,0,0,0.22,0.78,1.0,0.78,0.22]$

$Poss(y) := \Pi_{more\_or\_less(NO)} = [0,0,0,0.47,0.88,1,0.88,0.47,0,0,0]$

Similarly, a two dimension implication matrix $R_{X \to Y}$ can be evaluated using Lukasiewicz's implication operator (i.e., $A \to B = \min(1, 1 - a_i + b_j)$)

$$R = \begin{bmatrix} 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 0.78 & 0.78 & 0.78 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 0.78 & 0.78 & 0.78 \\ 0.22 & 0.22 & 0.22 & 0.69 & 1.0 & 1.0 & 1.0 & 0.69 & 0.22 & 0.22 & 0.22 \\ 0.0 & 0.0 & 0.0 & 0.47 & 0.88 & 1.0 & 0.88 & 0.47 & 0.0 & 0.0 & 0.0 \\ 0.22 & 0.22 & 0.22 & 0.69 & 1.0 & 1.0 & 1.0 & 0.69 & 0.22 & 0.22 & 0.22 \\ 0.78 & 0.78 & 0.78 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 & 0.78 & 0.78 & 0.78 \end{bmatrix}$$

with the composition relation defined in eqn 3.11, and A fuzzy input A' = "very positive_weak", A fuzzy output B'≈"normal" can be inferred using R

$$\begin{aligned}\mu_{A'\circ R} &= MAX(MIN(\mu_{A'}(x),\mu_R(x,y))\\ &= [0,0,0,0,0,0,0.05,0.61,1.0,0.61,0.05]\circ R\\ &= [0.22,0.22,0.22,0.61,0.88.1.0,0.88,0.61,0.22,0.22]^{-1}\end{aligned}$$

Through the above two examples it can be observed that-: (1) in application of CRI it is not necessary to have all antecedent of a rule matched EXACTLY so that the consequent of the rule can be hired, such as in the case of a hedge or unlimited number of hedges can be combined into the fuzzy statements. It implies two advantages of using CRI: great expression power; and tolerance of knowledge gap. (2) implication operators play an important role in the overall performance of a fuzzy decision process. As in the second example, all membership values in the output vector are greater than the values of desired fuzzy label. These observations will be discussed in detail in Chapter 6.

Nevertheless, fuzzy reasoning (CRI) offers an effective tool for proceeding reliability performance prediction under the fuzzy environment. In the next section, a case study of using FST and FR to predict individual device and human reliability performance by means of device failure possibility, maintenance time, human error possibility are presented.

3.6. Case Study

The validation of the proposed fuzzy reliability prediction framework is examined in this section by using the developed Fuzzy Rule Based Expert System Shell(FRBESS). Reliability Test System (RTS) (presented in Appendix III) is employed for this purpose. The main reason to adopt RTS as the case for test is that it has the consistence with the following chapters where we will further examine the validation of fuzzy system reliability computation and its application to electric power generating system reliability. It must be pointed out that the some of data in this section are artificially assigned, such as the situational factors of the units.

3.6.1. Modelling Consideration

There are 32 units in RTS. Among the units those bear with the same capacity are classified into the same category. The associated reliability data are unit failure rate (λ), Mean Time To Repair (MTTR), Scheduled Maintenance Time (SMT), and Forced Outage Rate (FOR) which can be obtained from λ and MTTR (see Appendix III).

For simplicity but without losing generality, a group of six 50 MW hydro units is selected for study. If it is assumed that each unit in the group has exactly same design quality, reliability characteristics, and use conditions, thus the case is simplified to study a unit in this group. The aim of the study is to evaluate failure possibility, maintenance time, and human error possibility of this unit with the available data which are given in Table 3.2.

It is assumed that a limit number of the situational factors have significant influence on the unit reliability performance. All the other factors as they were stated in Figure 3.5, 3.6, and 3.7 are ignoble for the reason of less significant adjustment effect. This assumption makes effective knowledge pruning so that it will greatly benefit the computation aspect. Further assumption is made on the pruned knowledge tree that expert judgmental knowledge can directly apply on all variables listed in Table 3.2. Therefore these prediction variables are regarded as the "basic variables" whose values can be retrieved from the users.

The values of basic variables are distinguished into three commonly used format, namely natural language expression, numerical interval and numerical singleton as they are shown in table 3.2. FRBESS can accommodate all three type of data by using a "converter" to convert numerical data into a possibility distribution, and *vise verse*. Furthermore, FRBESS also has the ability to convert an inferred possibility distribution to its corresponding natural language expression upon to the request (see Chapter 6).

For comparison, the original non-fuzzy crisp data and the fuzzy data of the two cases are listed together. Column 1 of table 3.2 lists the assigned non-fuzzy crisp data, in which a situational factor, say electrical defect, has the adjustment multiplier 2.5 means that it has the positive effect on the failure of the unit with the value 2.5 as the degree of such effect. Similarly, a factor " Variance of maintenance" has the negative effect on the unit failure with the degree of 0.5.

The considerations are on defining the proper universe of discourse and fuzzy terms set on these universe of discourse.

<u>The universe of discourses</u>

The universe of discourse is the particular range of linguistic variables that we are interested in. It is the part that the defined fuzzy set will refer to. For the basic estimate failure rate of the studied unit in RTS, we could sensibly choose the universe of discourse between 10^{-3} to 10^{-5} (time per hour). Since most of failure frequencies for this type of unit have the failure rate in this range. Moreover, a smaller range (if it is applicable) in general will give a sensible indication as well as the computation efficiency. Similarly, we could choose the universe of discourse between 0.1 to 10 for the combined situational factors, since the situational factors are the multiplier to adjust the basic estimation and its values are normally within this range except under some extraordinary situation such as the lunar operation which is inapplicable in this case. Therefore, it is reasonably to define the universe of discourses as:

X={device failure possibility, basic failure estimation, human error possibility, basic error estimation; $x \in [10^{-3}, 10^{-5}]$/p.h.}

Y={device maintenance time, basic maintenance time estimation ; $y \in [1, 100]$ hour}

RTS 50MW High Unit	Original Values	Case 1	Case 2
Unit Failure Possibility			
(1) The Basic Estimation	0.0001/h	moderate	moderate
(2) The Situational Facor			
Electrical Defect	2.5	quite (positive_strong)	[4, 5]
Thermal Defect	2	more_than (positive_weak)	3
Variance of Weather	2	more_than (positive_weak)	3
Variance of Maintenance	0.5	nagetive_weak	-3
Unit Maintenance Time			
(1) The Basic Estimation	20(h)	less_than (between_medium_and_long)	[6, 7]
(2) The Situational Factor			
Fault Detection	2	more_than (positive_weak)	[3,4]
Removal, Fix & Installation	1.7	positive_weak	positive_weak
Preparation	0.5	nagative_weak	-3
Maintenance Training	0.8	less_than (normal)	less_than (normal)
Part Stock Planning	1.5	less-than (less than (positive_weak)	2
Human Error Possibility			
(1) The Basic Estimation	0.0001/h	moderate	moderate
(2) The Situational Factor			
Competence	0.5	nagative_weak	-3
Physilogical Stress	1.2	more_than (more_than (normal))	1
Workload	2	more_than (positive_weak)	[3, 4]
weather	2	more_than (positive_weak)	[3, 4]

Table 3.2 The Data List For RTS Hydro Unit Reliability Prediction

Z1={internal stress, external stress, variance of active maintenance, variance of maintenance administrative; $z1 \in [10^{-1},10]$}

Z2={electrical defect, thermal defect, variance of weather, variance of maintenance, fault detection, removal, fix & installation, preparation, maintenacer training, part stock planning; $z2 \in [0.3, 3]$}

The universe of discourse then be mapped to an eleven elements arbitrary set by using eqn 3.3. As an example, let a=-5 and b=15 the universe of discourse of the internal stress can be transferred from range [0.1,10] to [-5,5]. This process makes sure that the fuzzy set defined on the universe of discourse will have more sensible linguistic meaning, say, a fuzzy set could be defined as "positive_strong" if its grade of membership is zero on the negative axis and is great than zero on the positive axis. The inferred result then can be transferred back to its original universe of discourse whenever it is necessary by using the reciprocal function of eqn 3.3.

Linguistic terms sets

On the defined arbitrary universe of discourse, the vocabulary of fuzzy sets (primary terms set) are defined as they are illustrated in Figure 3.10. One of consideration in defining terms set is that the fuzzy sets must overlap. This means that there are some failure possibility that are not strictly 'moderate', say $\lambda=10^{-4}$. Whatever rules apply to low failure possibility are likely to have a degree of validation for the category "moderate" too. This will ensure that a rule based predictor using CRI would trigger more than one rule at a time, with a reduced effect for those rules which have low degrees of validity.

3.6.2. Prediction By Using FRBESS

FRBESS is a fuzzy rule based expert system shell which is developed to accommodate and evaluate imprecise information based on the principles of fuzzy sets theory and fuzzy reasoning. It consists three main modules: (1) an interpreter; (2) a fuzzy rules compiler; (3) an inference mechanism. The main procedures of predicting reliability performance of RTS hydro unit are illustrated below. The detailed functions and the design aspects of FRBESS are referred in Chapter 6.

Rule & Data Interpretation

To predict the failure possibility of a hydro unit, the first step is to load the rule base and data base into FRBESS. The rule base for predicting reliability performance of the hydro unit is presented in appendix III, where rules are in MACSYMA's list format which is the same as LISP format. All rules are in "IF-THEN" format and the antecedents of a rule are linked by "AND" connector. The rules are grouped into the named rulesets (see appendix III). The data base contains the definition of the universe of discourse and fuzzy terms sets as they are presented in Figure 3.10. Once the knowledge base are loaded, FRBESS then translate all linguistic and numerical expressions into the form of discrete possibility distributions by using the rule interpreter and information processor of FRBESS.

Determining reasoning path

The next procedure is to determine the reasoning sequence. FRBESS provides a built-in facility based on the backward chaining strategy to construct reasoning path using the rule base loaded in the working memory. The method of determining reasoning path can be briefly explained by using the rules of predicting the unit failure possibility. First of all, it is to determine the "goal", say, The unit failure possibility, FRBESS then search the rule base to find the ruleset which has the consequent statement " Failure possibility". If there is one then put it into the empty path list in the working memory. For the ruleset being hired, FRBESS then search its antecedents part and triggered the first antecedent. After searching the rule base if it finds another ruleset whose consequent part matches this antecedent then put this ruleset into the path list as the first element, otherwise put the antecedent into the open list. This procedure repeats until all rulesets required for predicting "goal" are placed in the path list with the sequence. In the case of RTS hydro unit with the "goal" determined as Failure Possibility FRBESS generates 3 lists as

OPEN =[electric_defect, thermal_defect, variance_of_weather, variance_of_maintenance, basic_failure_estimation]

CLOSE=[]

PATH=[internal_stress, external_ stress, failure_possibility]

<u>Compile and aggregate rules</u>

Once the path list is determined, the rules of each ruleset in the path list are then compiled into relational matrices form, and aggregate these matrices into a single matrix for each ruleset using the methods described in the last section.

<u>Control of reasoning</u>

The control of reasoning is carried out by using three lists generated by "chaining" command. As for the example of hydro unit failure possibility prediction, FRBESS first will put the first ruleset "internal stress" in the path list into the working memory and check up whether its two antecedents " electric defect " and "thermal defect" are the member of the open list. If they are then FRBESS will first search the data base to find data, if it succeed then FRBESS will carry out the reasoning procedure by the commend "infer" otherwise FRBESS will prompt user to supply the data. Once the "internal stress" is inferred then FRBESS will move it away from the path list and select the first element in the new path list--this time is "external stress" and repeat the above procedure until the path list is empty. Thus, the "goal" is achieved.

For demonstration, a consultation session of predicting RTS hydro unit failure possibility (in case 1) is printed and presented in Figure 3.12.

3.5.3. Results

The results of predicting RTS hydro unit reliability performance by using FRBESS are presented and discussed in comparison with the result obtained by using the probabilistic techniques as described in Chapter 2.

CASE 1

(a) The inferred failure possibility of hydro unit is [0, 0, 0, 0, 0, 0, 0.22, 0.22, 0.78, 1.0, 0.22], its corresponding natural language expression is "failure possibility of the unit is between_moderate_and_high" which is obtained by using the least distance method, and its defuzzified crisp value is 8.31 which is corresponding to 4.6×10^{-4}/per hr. by using the centre of gravity method.

(b) The inferred maintenance time of hydro unit is [0, 0, 0, 0, 0.22, 0.22, 0.50, 0.78, 0.78, 1, 0.33], its corresponding natural language expression is "total maintenance time of the unit is between_medium_and_long", and its defuzzified crisp value is 7.6 which is corresponding to 34 hr..

(c) The inferred human error possibility on hydro unit is [0, 0, 0, 0.5, 0.5, 1, 1, 1, 0.78, 0.33, 0.33, 0], its corresponding natural language expression is " human error possibility of the unit is moderate", and its defuzzified crisp value is 6.6 which is corresponding to 2.1×10^{-4}/per hr..

CASE 2

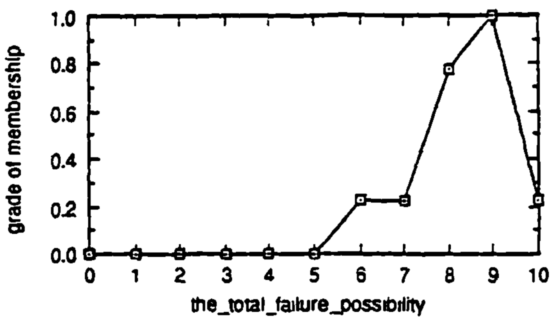
(a) The inferred failure possibility of hydro unit is [0, 0, 0, 0, 0, 0, 0.22, 0.50, 0.50, 1, 1], its corresponding natural language expression is " failure possibility of the unit is high", and its defuzzified crisp value is 8.6 which is corresponding to 5.25×10^{-4}/per hr..

(b) The inferred maintenance time of hydro unit is [0, 0, 0, 0, 0.50, 0.50, 0.33, 0.78, 0.78, 0.50, 0.22], its corresponding natural language expression is " total maintenance time of the unit is between_medium_and_long", and its defuzzified crisp value is 6.9 which is corresponding to 24 hr..

```
macsyma-417
This is Macsyma 417.100 for SPARC Series Computers.
Copyright (c) 1982 Massachusetts Institute of Technology.
All Rights Reserved.
Enhancements (c) 1982, 1991 Symbolics, Inc. All Rights Reserved.
Type "DESCRIBE(TRADE_SECRET);" to see important legal notices.
Type "HELP();" for more information.

Checking password file: /usr/local/lib/macsyma_417/system/passwd-1392550124-417.text
(C1) FRBESS (CONSULT);

**********************************************************************
*            FUZZY RULE BASED EXPERT SYSTEM SHELL                    *
*                        version 1.0                                 *
*                             by                                     *
*                         Lei   Wang                                 *
*                           1991                                     *
**********************************************************************

FRBESS ==> load(RTSunit_prediction.db, RTSunit_prediction.rb);

*** file RTSUNIT_PREDICTION.DB is loaded
*** file RTSUNIT_PREDICTION.RB is loaded

FRBESS ==>determine(the_failure_possibility);

*** the goal to be deducted is : the current goal ==> THE_FAILURE_POSSIBILITY

FRBESS ==> chaining(RTSunit_prediction.rb);

***OPEN=[electric_defect, thermal_defect, variance_of_weather,
variance_of_maintenance, the_basic_failure_estimation]

*** CLOSE=[]

*** PATH= [internal_stress, external_stress,
the_failure_possibility]


FRBESS ==>compile(path);

*** Select the implication operator  for generating fuzzy relational matrix, chose either 1, 2, 3, or 4
*** 1. Mamdani's 2. Lukasiewicz's 3. Gaines-Rescner 4. Godel
3;

*** relation arrays for all rulesets in the path list are generated.

FRBESS ==> infer(goal);

*** what is the_comparative_influence of electric_defect?
quite(positive_strong);

*** what is the_comparative_influence of thermal_defect?
more_than(positive_weak);

*** the_comparative_influence of internal_stress is deducted:
[0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.50, 0.78,0.78,1.00,1.00]

*** what is the_comparative_influence of variance_of_weather?
more_than(positive_weak);

***what is the_comparative_influence of variance_of_maintenance?
why;

***The reason for asking question is that the ruleset "the_comparative_influence of external_stress" is currently
***being hired. It has already benn established that
***Hypothesis:    the_comparative_influence of variance_of_weather
***It is aid in concluding the subgoal "the_comparative_influence of external_stress" by determining
***Hypothesis:    the_comparative_influence of variance_of_maintenance
***what is the_comparative_influence of variance_of_maintenance?
nagetive_weak;
```

Figure 3.9 Trace Of A Computing Session Of Predicting RTS Test Unit Failure

```
macsyma-417
*** the_comparative_influence of external_stress is deducted:
[0.00. 0.00. 0.22. 0.22. 0.50. 0.50. 0.50. 0.22.0.22.0.22.0.22]

*** what is the_basic_failure_estimation?
moderate;

*** The goal "the_failure_possibility" is deducted:
[0.00. 0.00. 0.00. 0.00. 0.00. 0.00. 0.22. 0.22. 0.78. 1.00. 0.22]

FRBESS ==>compress(goal);

*** The compressed goal is: 8.31

FRBESS ==>express(goal);

*** The goal is expressed approximately as:
the_failure_possibility of the unit is between_moderate_and_high

FRBESS ==>plot(goal);
```




```
FRBESS ==>save(%, testsession2);

*** File saved as /users/keag/wang/FRBESS/test/testsession2

FRBESS ==>bye;

*** Exit consulting session. GOOD BYE
*** Time= 2876956 msecs

(C2)
```

Figure 3.9 Continued ...

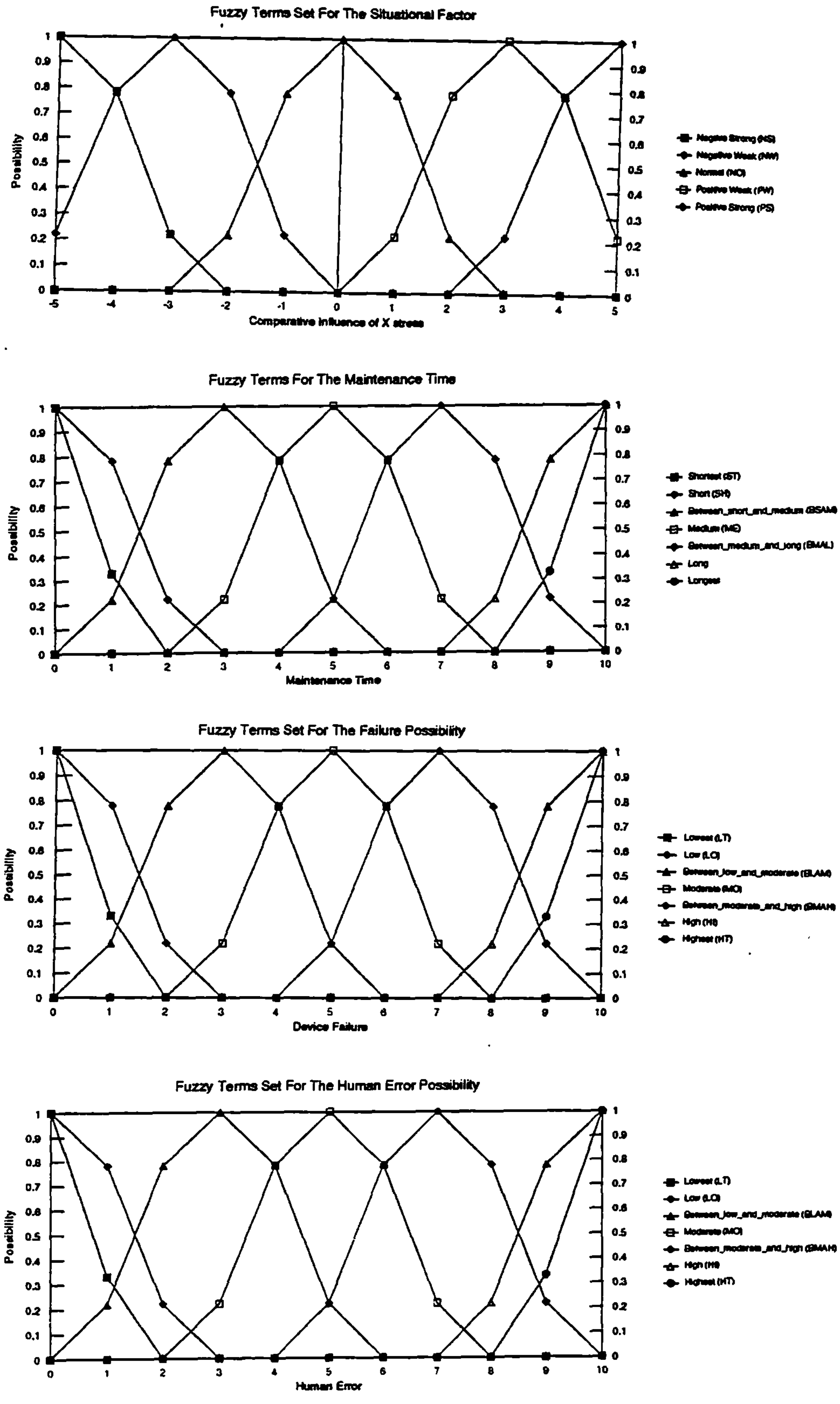


Figure 3.10 Fuzzy Terms Sets Definition For RTS Test Unit

(c) The inferred human error possibility on hydro unit is [0, 0, 0, 0.22, 0.5, 1, 1, 0.78, 0.78, 0.33, 0.33,], its corresponding natural language expression is "human error possibility of the unit is moderate", and its defuzzified crisp value is 6.4 which is corresponding to 1.9×10^{-4}/per hr..

By using the data in the first column of table 3.2, the results can be obtained using the traditional method. For failure possibility it is 5×10^{-4}/per hr., and 40.8 hr. for the maintenance time and 2.4×10^{-4}/per hr. for human error possibility. It is interesting to observe that the results inferred by using fuzzy reasoning are quite close to the results obtained by the traditional method. Only one exception in this study is that in case 2 the deducted maintenance time is about 50% of the value obtained by traditional multiply function . Therefore, it can confidently declare that the proposed fuzzy reliability prediction model is able to give the effective indication of reliability performance, and it has good compatibility with the traditional probabilistic model.

3.7. The Concluding Remarks

Most of the preliminary sections were concerned with the importance of human judgmental knowledge in reliability prediction, especially when varies situational adjustment factors are conducted.

The proposed approach is an attempt to model the knowledge of reliability engineer's predicting process under the fuzzy environment by using linguistic description, fuzzy inference techniques based on Fuzzy Sets Theory and Fuzzy Reasoning. The reliability performance are evaluated in three aspects, namely device failure, device maintenance and human error, which give the complete reliability indications. To test the validation of the proposed model a case study is conducted. The result proves that the fuzzy model delivers appropriate conclusion.

Chapter Four

Fuzzy Knowledge Based System Reliability Evaluation

4.1 Introduction

One of the challenging engineering endeavours of the past three decades has been the design and development of reliable large-scale systems for space exploration, military applications, power distribution and commercial operations. The design of such systems, unlike the design of individual devices, involves the broader aspects of organising composite equipment, operating and maintenance schedules, and the skills required to ensure system performance as an unified entity. System reliability performance is of primary concern and, therefore, the consequence of failure must be evaluated adequately.

Human reliability engineer's role in reliability prediction has been discussed and their empirical knowledge to aid predicting individual device reliability has been modelled and evaluated in the last chapters. To integrate these individual devices reliability so that the overall reliability performance of a complex system can be obtained, it demands to develop an appropriate model by which the inferred fuzzy individual devices reliability indices can be accommodated and processed. Such fuzzy model shall be able to deliver the adequate information at system reliability level.

This chapter presents two approaches to evaluate system reliability based on the inferred individual device reliability indices. A fuzzy arithmetic based system reliability combination model is discussed first. Some relevant fuzzy concepts are introduced which form the foundation for the proposed approach. The second part of this chapter presents a fuzzy knowledge based system reliability combination model. The fuzzy technique employed are fuzzy logic operators and compositional rule of inference, which were outlined in chapter 3.

4.2 Overviews of Current Approaches To Fuzzy System Reliability Calculation

To the author's knowledge Noma was the first one who introduced the newly emerged fuzzy set theory into reliability evaluation in 1981[66]. Since then the application of FST to reliability analysis has attracted many researchers and it has gone through a substantial development. A brief survey of some popular approaches to fuzzy reliability analysis are presented below:

Noma was the first one who formulated the initial statement of fuzzy reliability in 1981 by using the concept of fuzzy probability[66]. Not much different to the conventional reliability, in his approach he considered system failure is a random event and the subjective description like " a device fail to serve its function is probably" where the term 'probably' is a fuzzy restriction on the probability space. System reliability calculation was through the extension principle by using the probability "AND", "OR" combination rules.

Sugeno and Onisawa proposed a fuzzy fault tree analysis model in 1984[81]. In this model a concept " Failure Possibility" is expressed as a possibility distribution of which its parameters determined by three points estimate failure rate. The centre estimate failure rate was then classified into 10 groups. Each group has a qualitative label like "probable", "improbable", etc.. The idea behind is that even the probability is small, the chance of a device failure(possibility) still could be high. This assumption is in accordance with the probability and possibility consistence principle. System reliability calculation is through a pair of T-norm and T-conorm operators which are derived using the extension principle. The model distinct to other approaches in its attempt to use a conceptional measure "possibility", which has nothing to do with the familiar concept like probability, frequency, etc.

Singer proposed a simple fuzzy fault tree analysis model[79], where a reliability index, say, failure rate is modelled as a LR type fuzzy number. System reliability calculation is then by using the extension principle to calculate the parameters of fuzzy number. The result is also a LR-type fuzzy number.

Kauffman proposed a generalised fuzzy reliability model in which the concepts like "survival possibility" and "possibility of failure" were defined similarly to eqn 2.6 and 2.7 respectively. With understanding of the fact that the reliability source information is obtained from human experts and it is subjective therefore, Hence, failure rate is defined as a trapezoidal fuzzy number rather than a crisp number. In his approach the system reliability calculation is obtained by extending the classical reliability combination rules into a fuzzy discourse. Calculating the parameters of fuzzy device failure rate yields the system reliability which is also in a trapezoidal form.

By reviewing the current approaches to the system reliability calculation it is observed that-:(1) with the recognition of the fact that the reliability information are mostly subjective in nature, the basic reliability indices are modelled by a well-formed parametric fuzzy number. e.g., LR type, triangular and trapezoidal fuzzy number. (2) Fuzzy extension principle based arithmetical operators are intensively used for system reliability calculation.

2.2.1 The Terminology of Fuzzy Arithmetic

The author's initial research effort on system reliability calculation was conducted on developing a fuzzy arithmetical reliability calculator, which followed the current research trend. The motivation of developing a fuzzy arithmetic system reliability evaluation technique laid on:-(1) system reliability evaluation involves combining many individual device reliability indices. The combination process inevitably invokes intensive computation. Fuzzy arithmetic technique has been proved that it is a efficient tool for such task[46,47]. (2) Although the technique has been applied to the reliability field, it is still a relatively new area in which there are many problems to be solved, e.g., how to define a reliability index using a appropriate fuzzy number, definition of fuzzy reliability combination rules etc..

To illustrate the fuzzy arithmetical system reliability calculation, the terminology of fuzzy arithmetic such as *possibility theory*, *linear parametric fuzzy number* and *the extension principle* which were not covered in chapter 3 are introduced in this section.

α-cut of fuzzy set

The relation of ordinary set and fuzzy set can be represented by α-cuts of the fuzzy set. The α-cut of a fuzzy set, defined as $A\alpha$, is a ordinary set which is defined as

$$A_\alpha = (x|\mu_A(x) > \alpha, \alpha \in [0,1], x \in X) \qquad \text{eqn 4.1}$$

$A\alpha$ is an ordinary set of which the element has its membership value greater than some threshold α, $\alpha \in [0, 1]$. By introducing the α-cut a fuzzy set can be translated to a

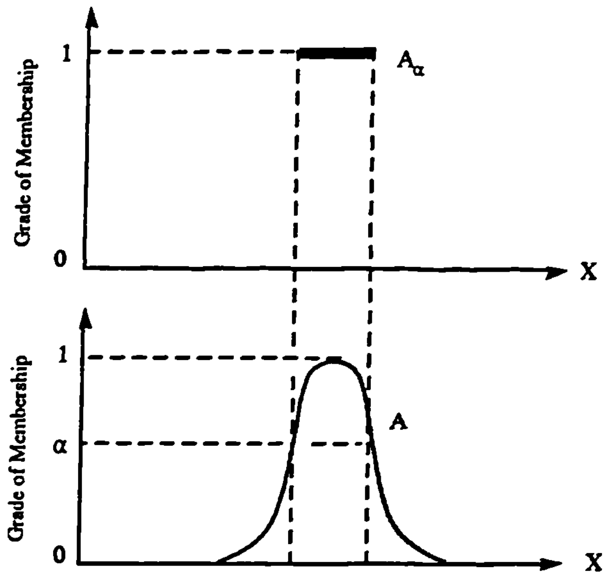


Figure 4.1 The Relationship Between The Ordinary Set and Fuzzy Set

ordinary set and *vice versa*. The relation of the fuzzy set and ordinary set is demonstrated in Figure 4.1.

Possibility theory

Possibility theory is a diverse of fuzzy set developed by Zadeh in 1978[101]. The following is Zadeh's powerful presentation:

Let Y be a variable taking value in X; then a possibility distribution, P(y), associated with Y may be viewed as a fuzzy constraint on the values that may be assigned to Y. Such a distribution is characterised by a possibility distribution function which associates with each the " degree of ease" or the possibility that Y may take X as a value.

From the definition given by Zadeh, it is clear that a possibility distribution reflects the constraint on the values of Y and it is a special type (i.e., the universe of discourse is the real line) fuzzy set of which the membership function is coincide with the possibility distribution, as shown in chapter 3. In some cases, the constraint on the values of Y is physical in origin; In many cases, however, the possibility distribution that is associated with a variable is epistemic rather than physical. A basic assumption in fuzzy logic is that such epistemic possibility distributions are induced by propositions expressed in a form of natural language. Hence, it provides an useful tool to represent the vagueness associated with the linguistic variables.

Fuzzy numbers

A fuzzy number is a number that is characterised by a possibility distribution or is a fuzzy subset of real numbers. In general, a fuzzy number is both a normal and convex fuzzy subset of real line. A fuzzy set A is said to be normal if one of its element has the highest grade of membership, that is, $\mu(x)=1$. If the universe of discourse is the set of real numbers and fuzzy subset A is monotonically decreasing on its right side sharp and monotonically increasing on its left side sharp, then fuzzy subset is said to be convex. Therefore, any fuzzy number is a possibility distribution. Simply examples of fuzzy numbers are fuzzy subsets of the real line labelled, for example the linguistic terms defined in chapter 3 such as *high*, *moderate*, *long*, *short*, etc.. A special case of a fuzzy number is an interval. Viewed in this perspective, fuzzy arithmetic may be regarded as a generalisation of interval arithmetic.

By the assumption that the reasonable approximation can be tolerated, fuzzy arithmetic can be simplified greatly and be more representiable for this task. It is expedient to represent the possibility distribution associated with a fuzzy number in a standardised form that involves a small number of parameters---usually two or three---which can be adjusted to fit the given distribution.

Linear parametric fuzzy number

In general two types of parametric fuzzy numbers are commonly used for information retrieval purpose: linear type and non-linear type. The non-linear fuzzy numbers like S and P type fuzzy numbers have been demonstrated in figure 3.3. Two widely used linear type fuzzy numbers are triangular (TFN) and trapezoidal (TrFN) fuzzy number. Their possibility distribution can be defined as a triplet (a,b,c) and a quadruplet (a,b,c,d) as follows:

$$
\begin{aligned}
TFN(X;a,b,c) &= 0 && \text{if } x < a \text{ or } x > c \\
&= \frac{x-a}{b-a} && \text{if } a \le x \le b \\
&= \frac{c-x}{c-b} && \text{if } b \le x \le c
\end{aligned}
\qquad \text{eqn 4.2}
$$

where a, c is the left and right end point, that is, membership of T(x=a=c) = 0 and b is the peak point at which T(x=b) = 1. Similarly TrFN can be represented by a quadruplet

$$
\begin{aligned}
TrFN(X;a,b,c,d) &= 0 && \text{if } x < a \text{ or } x > d \\
&= \frac{x-a}{b-a} && \text{if } a \le x \le b \\
&= 1 && \text{if } b \le x \le c \\
&= \frac{d-x}{d-b} && \text{if } b \le x \le d
\end{aligned}
\qquad \text{eqn 4.3}
$$

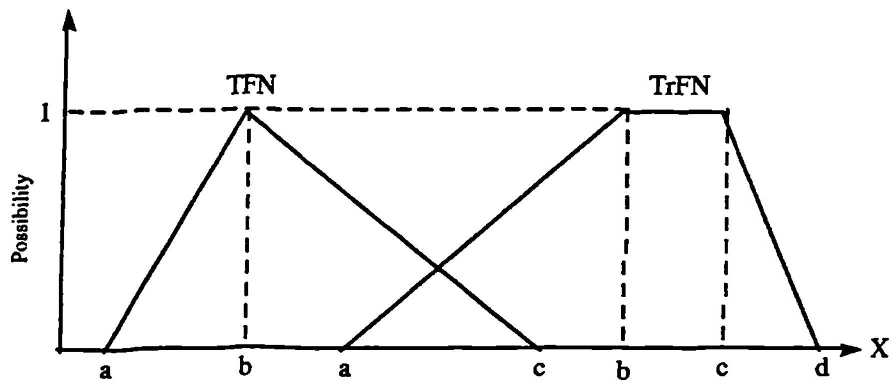


Figure 4.2 Triangular (TFN) and Trapezoidal(TrFN) Fuzzy Number

The parametric fuzzy numbers like TFN and TrFN are better described with the aid of a diagram as shown in Figure 4.2. It is clear that TFN is the exception of the TrFN, that is, if b=c then a TrFN become a TFN. Both TFN and TrFN has linear sharps so that the linear operations like addition, subtraction and scalar multiplication yield a TFN or TrFN respectively. However, the other operations like multiplication do not exactly given a TFN and the approximation can be defined with reasonable divergence.

The extension principle

One of the basic ideas of fuzzy set theory which provides a general extension of non-fuzzy mathematical concepts to fuzzy environments is the extension principle. This is a basic identity if a mapping or a relation to be extended from variable in the universe of discourse X to fuzzy subset of X, more specially, suppose that f is a mapping from the universe of discourse X to another universe of discourse and A is a fuzzy subset of X expressed as

$$A = \frac{\mu(x_1)}{x_1} + \dots\dots + \frac{\mu(x_n)}{x_n} \qquad \text{eqn 4.4}$$

then the extension principle asserts that

$$\begin{aligned} f(A) &= f\left(\frac{\mu(x_1)}{x_1} + \dots\dots + \frac{\mu(x_n)}{x_n}\right) \\ &= \frac{\mu(x_1)}{f(x_1)} + \dots\dots + \frac{\mu(x_n)}{f(x_n)} \end{aligned} \qquad \text{eqn 4.5}$$

Thus, the image of A under f can be deduced from the knowledge of the images of $X_1, \dots X_n$ under f. More simply, by extension principle fuzziness on a universe of discourse can "travel" to another universe of discourse if there is a functional relationship between the two sets, and this process can repeats as far as any inherent function relationship between the sets exists.

Fuzzy arithmetic

Fuzzy arithmetic on fuzzy numbers is accomplished by using the extension principle defined in eqn 4.4. Let * denote an arithmetic operation such as addition, multiplication, subtraction or division and C=A*B be the result of applying to the fuzzy numbers A, B. By the use of the extension principle it can readily establish that the possibility distribution function of A*B may be expressed in terms of those of A and B according to the relation

$$\mu_{C=A*B}(z) = \sup_{z=x*y}\{\min[\mu_A(x),\mu_B(y)]\} \qquad \text{eqn 4.6}$$

Let two TFN be represented by the triplets as A=(a1, b1, c1) and B=(a2, b2, c2), by eqn 4.1 and eqn 4.6 the addition of A and B can be derived as an example

$$A_\alpha = [(b1 - a1)\alpha + a1, c1 - (c1 - b1)\alpha] \qquad \alpha \in [0,1]$$
$$B_\alpha = [(b2 - a2)\alpha + a2, c2 - (c2 - b2)\alpha] \qquad \alpha \in [0,1]$$
$$\text{eqn 4.7}$$

where $A\alpha$ and $B\alpha$ are the α-cut sets of A and B respectively. By eqn 4.6 it has

$$\begin{aligned} f(A_\alpha + B_\alpha) &= \{[(b1+b2) - (a1-a2)]\alpha + (a1+a2), (c1+c2) - [(c1+c2) - (b1+b2)]\alpha\} \\ &= [(b-a)\alpha + a, c - (c-b)\alpha] \\ &= f(A+B)_\alpha \end{aligned} \qquad \text{eqn 4.8}$$

where a=a1+a2, b=b1+b2, c=c1+c2. Hence, the addition of TFN A and B is defined as the triplet

(1) addition A+B=(a1+a2, b1+b2, c1+c2) eqn 4.9

Similarly it has

(2) subtraction A-B=(a1-c1, b1-b2, c1-a2) eqn 4.10

(3) symmetric image -A =(-c1, -b1, -a1) eqn 4.11

(4) scalar production $k\times A=(k\times a1, k\times b1, k\times c1)$ eqn 4.12

It is shown that if A and B are TFN, then so are A+B, A-B etc.. Furthermore, the characterising parameters of A+B depend upon a very simple and natural way on those of A and B. However, this is not necessarily true for those non-linear mathematical operations. Non-linear operations can only be defined approximately [47] as

(5) product $A\times B \approx (a1\times a2, b1\times b2, c1\times c2)$ eqn 4.13

(6) inverse $A^{-1} \approx (\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1})$ eqn 4.14

(7) division $\frac{A}{B} \approx (\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2})$ eqn 4.15

(8) logarithmic $\ln A \approx (\ln a, \ln b, \ln c)$ eqn 4.16

(9) exponential $e^A \approx (e^{a_1}, e^{b_1}, e^{c_1})$ eqn 4.17

(10) n-th power $A^n \approx (a^n, b^n, c^n)$ eqn 4.18

Because of the reproducibility property of possibility distributions, the computational effort involved in the manipulation of fuzzy numbers is generally not much great than the required in the conventional interval arithmetic. As the given example was shown on using TFN, the operation on TFN is the operation on its three parameters. Perhaps this is the main reason why the current fuzzy reliability models favour fuzzy arithmetic method.

4.3 Fuzzy Arithmetical Reliability Calculation

Let TFN(λ ; a,b, c) denote a fuzzy constant failure rate which is modelled as a triangular fuzzy number, by the extension principle as stated in eqn 4.5 and eqn 4.17, Fuzzy Reliability can be defined mathematically as

$$\begin{aligned} \text{Fuzzy\_Reliability}(t) &= \max_{f=e^{-\lambda t}}\{\min[\text{TFN}(\lambda),t]\} \qquad t \geq 0 \\ &= \text{TFN}(e^{-ct}, e^{-bt}, e^{-at}) \end{aligned} \qquad \text{eqn 4.19}$$

where Fuzzy_reliability is a possibility distribution represented by the parameters of a fuzzy constant failure rate on the time space. It is clear that for each time interval Fuzzy Reliability is a TFN. Relatively, it can also define Fuzzy_Failure_Possibility as

$$\text{Fuzzy\_Failure\_Possibility} = \text{TFN}(1-e^{-ct}, 1-e^{-bt}, 1-e^{-at}) \qquad \text{eqn 4.20}$$

Some other reliability indices can also be obtained using the extension principle. For example , if $\text{TFN}(\lambda; a_\lambda, b_\lambda, c_\lambda)$ and $\text{TFN}(\gamma; a_\gamma, b_\gamma, c_\gamma)$ denote for fuzzy failure rate and fuzzy repair rate respectively, fuzzy availability and unavailability can be obtained as

$$\text{Fuzzy\_Availability} = \text{TFN}(\frac{a_\gamma}{c_\lambda + c_\gamma}, \frac{b_\gamma}{b_\gamma + b_\lambda}, \frac{c_\gamma}{a_\lambda + a_\gamma})$$

$$\text{Fuzzy\_unavailability} = \text{TFN}(\frac{a_\lambda}{c_\lambda + c_\gamma}, \frac{b_\lambda}{b_\gamma + b_\lambda}, \frac{c_\lambda}{a_\lambda + a_\gamma}) \qquad \text{eqn 4.21}$$

Reliability combination rules can also be extended to fuzzy reliability calculation by the extension principle. The classical probability logical connectors such as AND, OR, can be extended to fuzzy numbers as

(1) "OR" (series connected two independent devices)

$TFN_{failure}(F1;a1,b1,c1)$ OR $TFN_{failure}(F2;a2,b2,c2)$

$=TFN_{failure}(F1F2;\ a1 + a1 - c1 \times c2, b1 + b2 - b1 \times b2, c1 + c2 - a1 \times a2)$ eqn 4.22

$TFN_{reliability}(R1;a1,b1,c1)$ OR $TFN_{reliability}(R2;a2,b2,c2)$

$=TFN_{reliability}(R1R2;\ a1 \times a2, b1 \times b2, c1 \times c2)$ eqn 4.23

(2) "AND" (parallel connected two independent devices)

$TFN_{failure}(F1;a1,b1,c1)$ AND $TFN_{failure}(F2;a2,b2,c2)$

$=TFN_{failure}(F1F2;\ a1 \times a2, b1 \times b2, c1 \times c2)$ eqn 4.24

$TFN_{reliability}(R1;a1,b1,c1)$ AND $TFN_{reliability}(R2;a2,b2,c2)$

$=TFN_{reliability}(R1R2;\ a1 + a1 - c1 \times c2, b1 + b2 - b1 \times b2, c1 + c2 - a1 \times a2)$ eqn 4.25

The extension principle can apply to not only the well-formed parametric fuzzy numbers but also any type of possibility distributions which may be ill-formed. An interesting example is to obtain FOR(availability) in the case study of chapter 3., where the inferred unit failure rate and maintenance time are ill-formed as they were described in section 3.63, chapter 3. If the total maintenance time is equal to MTTR then fuzzy FOR for case 1 can be calculated as

$$\mu_\lambda(x) = [\frac{0}{1},\frac{0}{1.6},\frac{0}{2.5},\frac{0}{4},\frac{0}{6.3},\frac{0}{10},\frac{0.22}{16},\frac{0.22}{25},\frac{0.78}{40},\frac{1}{63},\frac{0.22}{100}] \quad x{:}x \times 10^{-5}/h$$

$$\mu_{MTTR}(y) = [\frac{0}{1},\frac{0}{1.6},\frac{0}{2.5},\frac{0}{4},\frac{0.22}{6.3},\frac{0.22}{10},\frac{0.50}{16},\frac{0.78}{25},\frac{0.78}{40},\frac{1}{63},\frac{0.33}{100}] \quad y{:}y\,(h)$$

$$\mu_{FOR}(z) = \max_{FOR=\frac{1}{\lambda \times MTTR+1}} (\min(\mu_\lambda(x),\mu_{MTTR}(y)))$$

$$= [\frac{0}{0.9999},\ldots,\frac{0.22}{0.9980},\ldots,\frac{1}{0.9618},\ldots,\frac{0.22}{0.9091}]$$

$$\approx [\frac{0.22}{0.998},\frac{0.22}{0.997},\frac{0.22}{0.996},\frac{0.50}{0.994},\frac{0.78}{0.990},\frac{0.78}{0.985},\frac{0.78}{0.975},\frac{1}{0.960},\frac{0.33}{0.940},\frac{0.22}{0.910}]$$

The obtained fuzzy FOR was approximated, e.g., let μ (0.9937)=μ (0.9901)=μ (0.9900). The disadvantage of computing non-format possibility distribution using the extension principle is obvious, as in the above example the concluded FOR distribution should consist 100 grade of memberships. In general a fuzzy arithmetic operation on a possibility distribution with n memberships yields n^2 memberships. Beside, any approximation introduced may cause the consequence of losing some useful information.

4.3.1 Converting Non-format Fuzzy Data To TFN

One particular problem founded during research is that an effective fuzzy arithmetic model demands that the subjective reliability source data are modelled as the well-format parametric fuzzy numbers. It assumed that the reliability experts should be able to estimate reliability data at device level and these information are in good format so that they can be easily processed in terms of fuzzy arithmetic. Unfortunately, this is not the case in most situations. As an example, by questioning the credit of such subjective estimation this study has lead to more deep level where the source of uncertainty of reliability data were relatively more clearly explored. As it has been discussed in chapter 3, the source of uncertainty has two-fold: The subjective estimated basic reliability data, and the varies situational adjustment factors. Understanding the fact that the natural language is the most nature and appropriate way for a human expert to express his empirical judgement, it has been established that the possibility theory based multi-dimensional fuzzy reasoning(CRI) is a suitable tool for evaluating those vague and

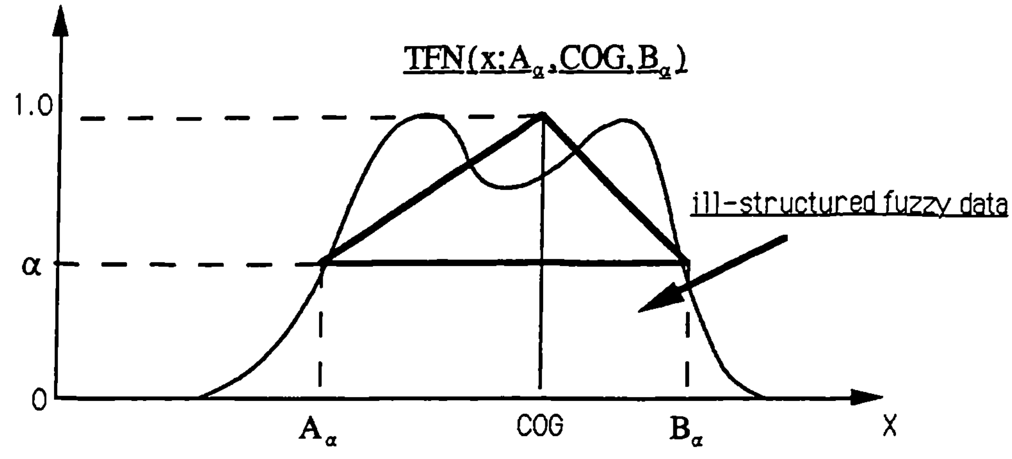


Figure 4.3 Converting An Ill-structured Fuzzy Data to TFN

imprecise information at device level. However, the inferred device reliability data are not well-formed fuzzy number in some cases. Rather, they could be any type of possibility distributions (see section 3.6.3, chapter 3).

An attempt to convert any-format fuzzy data to TFN has been made. By using α-cut and Centre of Gravity (COG) method (see chapter 6), a TFN type reliability data TFN(X; a,b,c) can be generated, where b is defined as COG and the two ends of a α-cut are b and c respectively. The converted data is an approximation but the important information are maintained. Most importantly, it provides a way to combine the model presented in last chapter with this approach for a complete fuzzy system reliability evaluation. The method of converting an any-format fuzzy data to TFN is shown in figure 4.3.

4.4 Fuzzy knowledge based System Reliability Calculation

Motivated by the successful application of fuzzy reasoning to industrial control, in which the control process were induced to a set fuzzy control rules. It is natural to adopt the idea of developing a fuzzy knowledge based system reliability model in which the fuzzy combination rules and its reasoning algorithm. The outline of the proposed model is presented graphically in figure 4.4

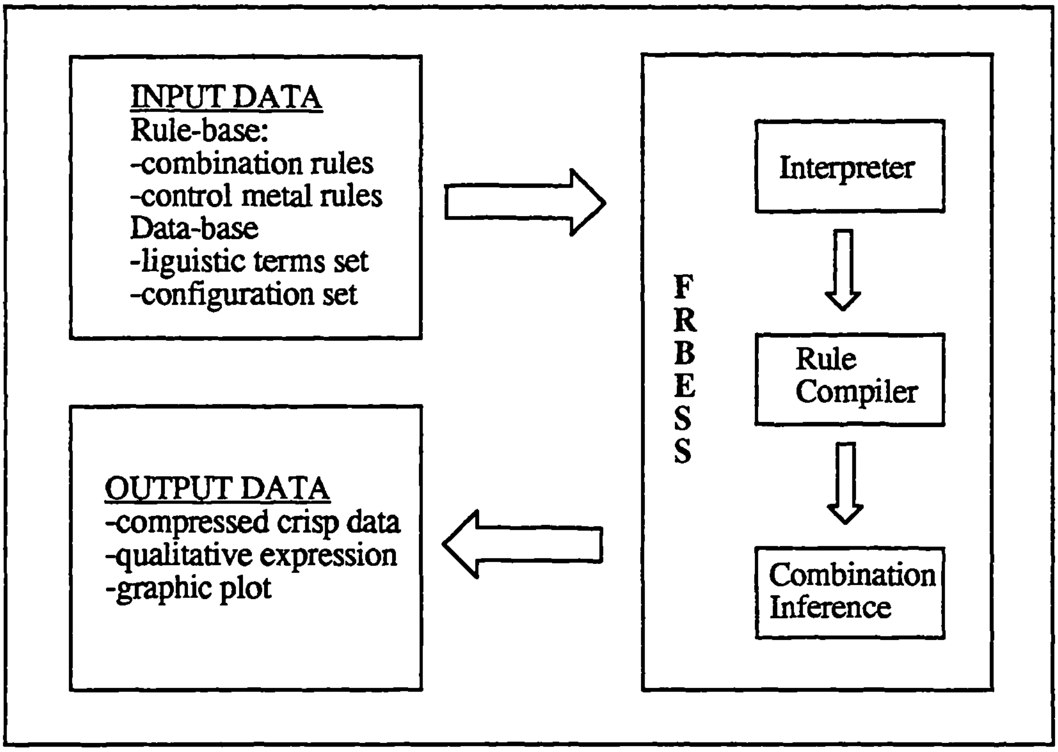


Figure 4.4 Fuzzy Knowledge Based System Reliability Evaluation Model

4.4.1 Fuzzy Reliability Combination Rules

Empirically, one can infer that the chance of both devices failure causing system failure is equal or less than the chance of each device failure; and the chance of either device failure causing system failure is equal or greater than the chance of each device failure. This empirically observation may be induced into a fuzzy rule form

IF Two devices A and B are in series connection

AND the chance of device A survive is *moderate_possible*

AND the chance of device B survive is *quite_possible*

THEN the chance of the combined system AB survive is *slightly_possible*

The first conditional statement of the above rule is deterministic meta-rule, which is designed for controlling the reasoning process. The remained statements are ambiguous, since it consists linguistic expressions like "moderate_possible", etc.. It has been stated in chapter 2 that a probability combination rule for two series connected devices reliability is the product of each device reliability, which is in accordance with the above statement. The process is rigorous if the available data are rigorous as well. However, it is not the case in this application as it has been argued thoroughly. Beside, it has been well argued in fuzzy control applications that even in the reality the input and output are deterministic in nature, when these information reflected to the human being's brain they become fuzzy information, e.g., high temperature, low pressure, etc.[54]. Human experts then adjust the obtained information in accordance with their own experience and knowledge, so that an appropriate decision can be made. By simulating a human expert's fuzzy reliability combination process, two sets of combination rules for series and parallel connected system reliability (survive) can be induced as they are presented in appendix IV.

Fuzzy reliability combination rules can be induced either by the reliability experts, or through the experimental method. The experimental method is by adjusting the input for the antecedents of a rule to examine the correspondence of the inferred consequence, and finally determine the most appropriate correspondence between the antecedents and the consequence of a rule.

Apart from reliability combination rules, failure frequency combination rules are frequently used as well in reliability analysis, particularly for Fault Tree Analysis(FTA) which is aimed to obtain frequency of occurrence of the top event. Such combination rules may be stated as

IF Two devices A and B are in parallel connection

AND The failure frequency of device A is *hourly*

AND the failure frequency of device B is *daily*

THEN the failure frequency of the combined system AB is *more than weekly*

Fuzzy combination rules for both series and parallel connected system failure frequency are induced and presented in appendix IV. The linguistic expressions such as *daily*, *moderate_possible* etc. are defined in figure 4.6.

4.4.2. Combining Individual Device Reliability Using FRBESS

The device reliability evaluation process using FRBESS has three stages: Interpret the linguistically expression embedded in fuzzy combination rules into their possibility distributions; compile fuzzy combination rules to generate their relational matrices by a chosen implication operator, and aggregate these matrices into a single rule-set matrix; infer system reliability by using a set of meta rules to control the reasoning sequence.

The data-base for combining system reliability contains three part of information: (1) linguistic primary terms definition; (2) reliability data of each individual devices in the system, which can be in the form of linguistically expression, numerical interval or a crisp value; and (3) configuration list in which it contains the information of how devices are connected. The rule-base contains (1) combination rules and (2) meta control rules. The processes of data interpretation, rule compiling and aggregating are the same as that of devices reliability prediction (see chapter 3). The combination reasoning process carries out using four lists, i.e., a path list which is the configuration list in the data-base; a close list which contains the name of those already being combined devices; an open list which contains the name of all devices in a system to be combined; and a current list which contains a set devices currently in process. A current list can be the path list, or any one of sub-list of the path list. Instead of generating by the build-in " chaining" facility of FRBESS as it is in device reliability prediction, the path list in reliability combination process is obtained from the data-base, and the other two lists are generated by sorting the path list. The path list plays an important role in the combination process. For example, suppose there are three devices A, B, and C. A and B are parallel connected and C is series connected to A and B, a typical path list for combining system ABC is in the form of

path=[c, [a, b]']

where a list with a quota means that all elements in the list are parallel connected, otherwise they are series connected. A sorting process then is used to re-order these elements in the path list by using the depth search techniques as

path=[[a, b]', c]

open=[a,b, c]

close=[]

The idea of sorting is to put the most nested sub-list of the path or any one of current list at the first priority to be processed. In the above example there has only one nested list so that the sorting process accomplished and the open list was also created. Fuzzy inference process can then be applied using the above three lists until the path list and the open list become empty.

4.4.3 Control of Reliability Combination Process

A combination rule in a rule-base can be described in the natural language form as

IF the chance of the current system survive is *any*

AND the chance of device X survive is *quite_possible*

THEN the chance of the newly combined system survive is *quite_possible*

Or it can be represented in an abstract form as

IF S is *any* and X is *quite_possible* then S' is *quite_possible*

In the above combination rules the string "the current system" represents the devices which were already combined. The initial state of the current system is set as null, which corresponds to a fuzzy term as "any". The control strategy of determining the combination sequence is explained as :- (1) select the first element in the path list, if it is a string then it means there has no list element in the path list and combination process can apply to the path list, otherwise if it is a list as to the above three device system it find lists [a,b]'; then (2) select the first element of this new list to examine whether the element is a list or a string. If it is a list then the selection process will repeat (1) and (2) until a string is found, otherwise if it is a string, say, 'a', then (3) retrieve its data from the data-base, if there is no data for 'a' in the data base then check the open list. If 'a' is in the open list then prompt the user to supply a data. (4) rule1 is hired and 'a' replaces X, Infer the current system 'S' by composite to the initial combination ruleset matrix; (5) combine all elements in the current list, i.e., 'a' and 'b', using meta rule for selecting either series or parallel combination ruleset. (6) once the list [a,b]' are combined, check the next element to the list, if it is string then replace the current list by this new list, say, path list and repeat (5) otherwise replace the list by a string which represents the inferred list and place it at the last place of the path list, also move 'a' and 'b' from the open list to the close list. (7) restart the process from (1) until all elements in the path list become string then combine these elements, and delete them from the path list. (8) Once the path and open list become the empty lists then quit the combination reasoning process. The above combination reasoning procedures can be organised by a set of meta rules. The combination sequence control algorithm is described in figure 6.7, chapter 6.

The control strategy for selecting of combination rules is relatively simple. There are two control rules for combining parallel and series system reliability: If there is a device list with a quota then the aggregated fuzzy relational matrix generated from the parallel combination rule-set should be invoked; otherwise if there is a device list without quota then the fuzzy series matrix is invoked. This control process is also implemented by meta rules. The detailed discussion of implementing combination control is presented in chapter 6.

4.5 Cases Study

Two cases are studied by using the proposed fuzzy knowledge system reliability evaluation model. The results of the study are then analysed in comparison with the classical probability combination method (see chapter 2) and fuzzy parametric system reliability combination method in section 4.2.

4.5.1 Modelling Considerations

Case one

The first case to be studied is the example system presented in figure 2.6 of chapter 2, where five devices formed a series-parallel mixed complex system. The assigned reliability for each device are:

$P_A=0.5$; $P_{B1}=P_{B2}=0.1$; $P_{C1}=P_{C2}=0.01$

The above data can be transfered to the universe of discourse "the chance of survive" using eqn 3.3 and fuzzification method (see chapter 6) as

$\mu_A(x) = [0.00,0.00,0.00,0.00,0.00,0.00,0.00,0.00,0.00,0.40,0.60]$ $x = 1,...,10$
$\mu_{B1}(x) = \mu_{B2}(x) = [0.00,0.00,0.00,0.00,0.00,0.00,0.00,0.00,1.00,0.00,0.00]$ $x = 1,...,10$
$\mu_{C1}(x) = \mu_{C2}(x) = [0.00,0.00,0.00,0.00,0.00,0.00,1.00,0.00,0.00,0.00,0.00]$ $x = 1,...,10$

The assigned reliability can also be fuzzified to form a triangular number TFN(x; a,b,c) by considering a 5% divergence so that they can be

$TFN_A(x;0.475,0.500,0.525)$; $TFN_{B1=B2}(x;0.095,0.100,0.105)$;

$TFN_{C1=C2}(x;0.0095, 0.010, 0.0105)$

The configuration list for this case is defined according figure 2.6 as

config:[[B1, C1], [A, [C1, C2]'], [B2, C2]]'

In this case it is aimed to combine all 5 devices to obtain the system survive possibility.

Case 2

In this case two groups of RTS units(see appendix II) are considered. They are 4 20 MW turbine units and 3 100 MW fossil steam units. The failure rate of 20MW units is obtained from RTS and the failure rate for 100MW units is modified as

$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0.0022;$ $\lambda_5 = \lambda_6 = \lambda_7 = 0.045$

Similarly, they can be transferred to the universe of discourse "the failure frequency" as

$\mu_1(x) = \mu_2(x) = \mu_3(x) = \mu_4(x) = [0.00,0.00,0.00,0.00,0.32,0.68,0.00,0.00,0.00,0.00,0.00]$
$\mu_5(x) = \mu_6(x) = \mu_7(x) = [0.00,0.00,0.00,0.00,0.00,0.00,0.00,0.30,0.70,0.00,0.00]$

These failure rate are fuzzified to be TFN by considering a 7 % divergence as

$TFN_{\lambda_1=\lambda_2=\lambda_3=\lambda_4}(x;1.86 \times 10^{-3},2.0 \times 10^{-3},2.14 \times 10^{-3})$
$TFN_{\lambda_5=\lambda_6=\lambda_7}(x;4.19 \times 10^{-2},4.5 \times 10^{-2},4.82 \times 10^{-2})$

It is assumed that all units in a same capacity group are series connected, and two groups are parallel connected. Hence, the configuration list for this case can be defined as

Config:[[u1, u2, u3, u4], [u5, u6, u7]]'

In this case it is aimed to combine 7 units to obtain the top event "system failure frequency".

4.5.2 Combination Reasoning Using FRBESS

After loading the data-base and the rule-base, the process of interpreting the data-base is automatically carried out by FRBESS. The first task of the combination reasoning is to compile and link SDIS (Self Defined Inference Sequence) control Algorithm by "switch" command. The next process is to sort the path list using the "sort" command. It is aimed to-:(1) place the most nested sub-list at the first place of a current list, and the second most nested list at the second place, and so on until the process priority is sorted; (2) always place the list elements before the string elements in a list. For case 1, the "sort" command will result as

path=[[[C1, C2]', A], [B2, C2], [B1, C1]]'

The process of compiling the rule-set generates three rule-set matrices: initial combination matrix, series combination matrix, and parallel combination matrix. The combination reasoning process is carried out then after, using the meta control rules to determine the sequence of devices to be combined to the current system and to select an appropriate connection matrix for inference. The combination sequence for case 1 is demonstrated below:

step1: path=[[[C1, C2]', A], [B2, C2], [B1,C1]]'; current list=[[C1, C2]', A];
step2: current list=[C1, C2]'; combine C1 with the current system(null) using initial matrix
step3: current list=[C2]'; combine C2 with the current system(C1) using parallel matrix
step4: current list=[A]; combine A with the current system(C1,C2) using series matrix
step5: path=[[B2, C2], [B1,C1], S1]'; current list=[B2,C2]; S1=result(C1,C2, A)
step6: current list=[B2,C2]; combine B2 with the current system(null) using initial matrix
step7: current list=[C2]; combine C2 with the current system(B2) using series matrix
step8: path=[[B1,C1], S1, S2]'; current list=[B1,C1]; S1=result(C1,C2); S2=result(B2,C2)
step9: current list=[B1,C1]; combine B1 with the current system(null) using initial matrix
step10: current list=[C1]; combine C1 with the current system(B1) using series matrix
step11:path=[S1, S2, S3]';current list=[S1,S2,S3];S1=result(C1,C2,A); S2=result(B2,C2);S3=result(B1,C1)
step12: current list=[S1,S2,S3]';combine S1 with the current system(null) using initial matrix
step13: current list=[S2, S3]'; combine S2 with the current system(S1) using parallel matrix
step14: current lsit=[S3]'; combine S3 with the current system(S1,S2) using parallel matrix

step15: path=[], open=[]; quit the combination reasoning process

For demonstration, the computer session of two cases studies are printed and presented in figure 4.5.

4.4.3 Results and Discussion

The results of calculating system reliability by using fuzzy rule-based combination model are presented and discussed in comparison with the results obtained by using fuzzy arithmetic model (section 4.2) and classical probability model.

<u>case 1</u>

The inferred system survive possibility is [0.00, 0.00, 0.00, 0.00, 0.22, 0.50, 0.60, 0.78, 0.33, 0.33, 0.33, 0.33]. Its corresponding qualitative expression is " the_current_state(survive) of system is quite_possible". By using COG method it results 6.24 which is corresponding to 0.014 after transferring back to its original universe of discourse.

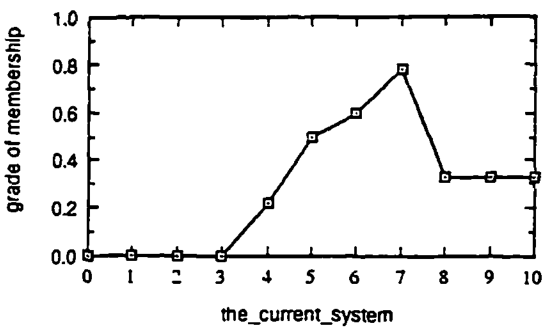
The calculated TFN by using egn 4.23 and eqn 4.25 is (0.01077, 0.01192, 0.01315). The calculated survive probability by using eqn 2.15 and eqn 2.17 is 0.01192.

<u>Case 2</u>

The inferred system failure frequency possibility is [0.22, 0.32, 0.68, 0.30, 1.00, 0.70, 1.00, 0.22, 0.00, 0.00, 0.00]. Its corresponding qualitative expression is " the_current_state(failure) of system is between_[weekly, monthly]". By using COG method it results 3.92 which is corresponding to 0.00096/ hr. after transferring back to its original universe of discourse.

The calculated TFN by using egn 4.23 and eqn 4.25 is (0.00092, 0.00113, 0.001385). The calculated system failure frequency by using eqn 2.14 and eqn 2.16 is 0.00113/ per hour.

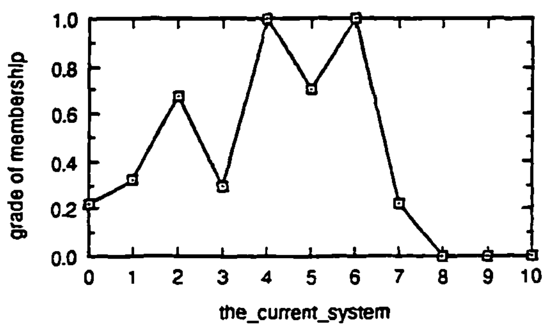
```
macsyma-417
Copyright (c) 1982 Massachusetts Institute of Technology.
All Rights Reserved.
Enhancements (c) 1982, 1991 Symbolics, Inc. All Rights Reserved.
Type "DESCRIBE(TRADE_SECRET);" to see important legal notices.
Type "HELP();" for more information.

Checking password file: /usr/local/lib/macsyma_417/system/passwd-1392550124-417.text
(C1) FRBESS (CONSULT);
*****************************************************************
*          FUZZY RULE BASED EXPERT SYSTEM SHELL                 *
*                      version 1.0                              *
*                          by                                   *
*                      Lei   Wang                               *
*                         1991                                  *
*****************************************************************

FRBESS ==> load(survive_combination.db, survive_combination.rb);

*** file SURVIVE_COMBINATION.DB is loaded
*** file SURVIVE_COMBINATION.RB is loaded

FRBESS ==>switch(SDIS);

*** SDIS is compiled and linked

FRBESS ==> sort(path)

*** PATH=[[[C1, C2]', A], [B2, C2], [B1, C1]]'

*** CLOSE=[]

*** OPEN= {C1, C2, A, B2, C2, B1, C1}

FRBESS ==>compile(rb_combination_survive);

*** Select the implication operator for generating fuzzy relational matrix, chose either 1, 2, 3, or 4
*** 1. Mamdani's 2. Lukasiewicz's 3. Gaines-Rescher 4. Godel
3;

*** relation arrays for all rulesets in RB_COMBINATION_SURVIVE are generated.

FRBESS ==> infer(system=null(open));

*** goal(system) archieved: the_current_state of system is
[0.00, 0.00, 0.00, 0.00, 0.22, 0.50, 0.60, 0.78, 0.33, 0.33, 0.33]

FRBESS ==>express(goal);

*** The goal is expressed approximately as:
the_current_state of system is quite_possible

FRBESS ==>plot(goal);
```




```
FRBESS ==>compress(goal);
```

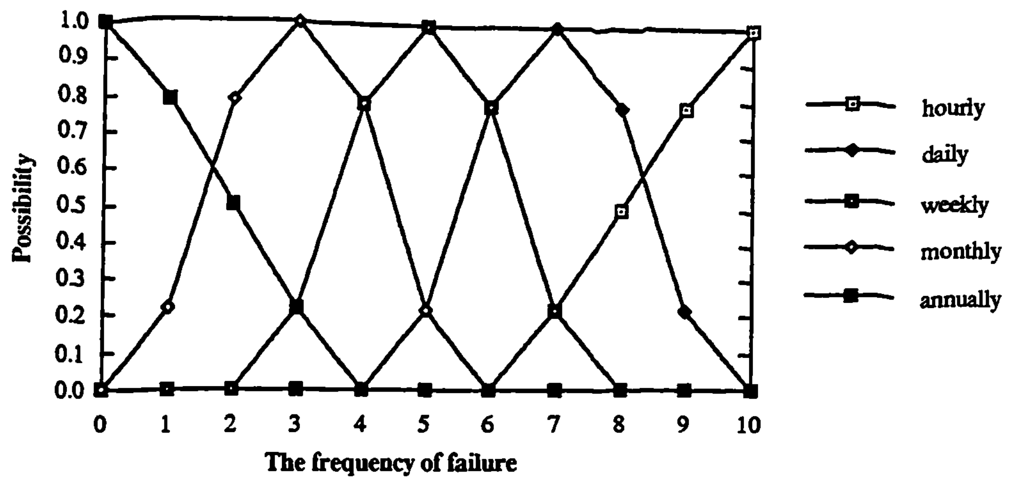
Figure 4.5 Trace Of A Computing Session Of Two Sample Systems Evaluation macsyma-417

```
FRBESS ==>save(%, testsession6);

*** File saved as /users/keag/wang/FRBESS/test/testsession6

FRBESS ==> reset();

FRBESS ==> load(failure_combination.db, failure_combination.rb);

*** file FAILURE_COMBINATION.DB is loaded
*** file FAILURE_COMBINATION.RB is liaded

FRBESS ==>switch(SDIS);

*** SDIS is compiled and linked

FRBESS ==> sort(path)

*** PATH=[[ U1, U2, U3, U4], [U5, U6, U7]]

*** CLOSE=[]

*** OPEN= [U1, U2, U3, U4, U5, U6, U7]

FRBESS ==>compile(rb_combination_failure);

*** Select the implication operator  for generating fuzzy relational matrix, chose either 1, 2, 3, or 4
*** 1. Mamdani's  2. Lukasiewicz's  3. Gaines-Rescher 4. Godel
3;

*** relation arrays for all rulesets in RB_COMBINATION_FAILURE are generated.

FRBESS ==> infer(system=null(open));

*** goal(system) archieved; the_current_state of system is
[0.22, 0.32, 0.68, 0.30, 1.00, 0.70, 1.00, 0.22, 0.00, 0.00, 0.00]

FRBESS ==>compress(goal);

*** The compressed goal is:  3.92

FRBESS ==>express(goal);

*** The goal is expressed approximately as:
the_current_state of system is between_[weekly, monthly]

FRBESS ==>plot(goal);
```

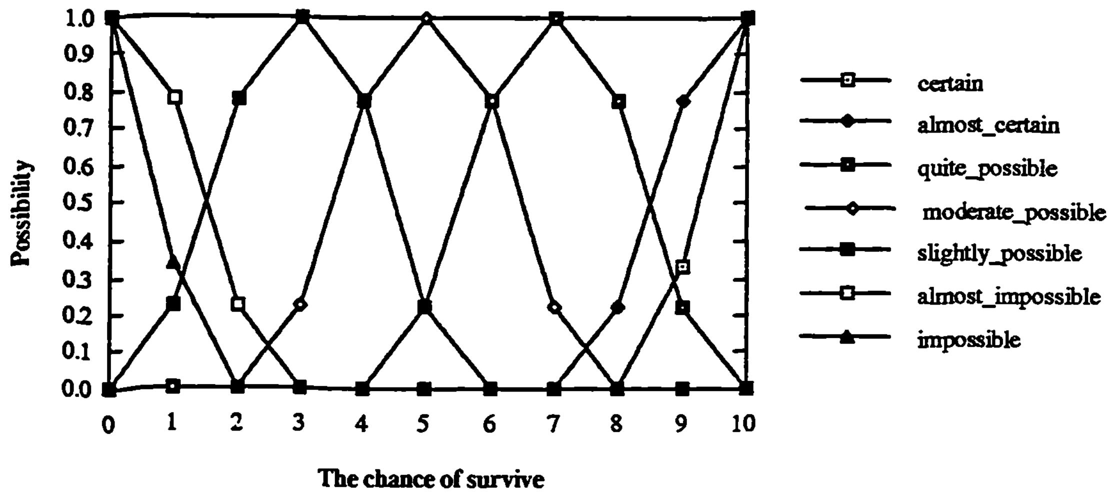



```
FRBESS ==>save(%, testsession7);

*** File saved as /users/keag/wang/FRBESS/test/testsession7

FRBESS ==>bye;

*** Exit consulting session, GOOD BYE
*** Time= 3695950 msecs

(C2)
```

Figure 4.5 Continued...



X = {failure rate, x $\in [10^{-5},1]$ / the failure number per hour}   Y = {the frequency of failure, y $\in [0,10]$}
y=alog(x)+b; a=2, b=10
hourly=[0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.22, 0.50, 0.78, 1.00]
daily=[0.00, 0.00, 0.00, 0.00, 0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00]
weekly=[0.00, 0.00, 0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00, 0.00, 0.00]
monthly=[0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00, 0.00, 0.00, 0.00, 0.00]
annually=[1.00, 0.78, 0.50, 0.22, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00]



X = {probability of survive, x $\in [10^{-5},1.0]$}   Y = {the chance of survive, y $\in [0,10]$}
y=a log(x) + b; a=2, b=10
certain=[0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.33, 1.00]
almost_certain=[0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.22, 0.78, 1.00]
quite_possible=[0.00, 0.00, 0.00, 0.00, 0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00]
moderate_possible=[0.00, 0.00, 0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00, 0.00, 0.00]
slightly_possibile=[0.00, 0.22, 0.78, 1.00, 0.78, 0.22, 0.00, 0.00, 0.00, 0.00, 0.00]
almost_impossible=[1.00, 0.78, 0.22, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00]
impossible=[1.00, 0.33, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00]

Figure 4.4 Linguistic Definition For The System Survive and The Failure Frequency

From the results obtained it is found that fuzzy rule-based combination model is a appropriate approach to calculate system reliability, since the COG results of both cases are quite reasonable in comparison with the results obtained from the classical probability combination method. The possibility distribution obtained in case 2 is less indicative, for it has more than one peak. It may be due to the large knowledge gap appeared in the rule-base. However, its qualitative expression obtained by using least distance method delivers good indication. On the other hand, it is not surprise to find that the results obtained by using fuzzy arithmetic method are well matched, since the operators were extended from the classical probability combination operators.

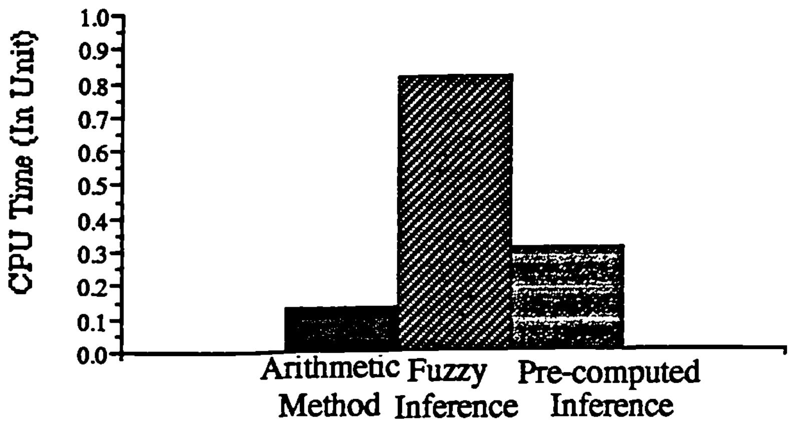


Figure 4.7 Benchmark Of Computational Effieiency Of Two Approaches

Another aspect of comparison is the computational efficiency of both arithmetic and fuzzy inference approach. Using case 1 as an example, the computing time using fuzzy knowledge based model is almost 8 times of the computing time using fuzzy arithmetic model(see figure 4.7. It is found that during a consultation session the most of computing time for fuzzy inference model are spent on rule interpretation and relational matrix generation. The computational efficiency of fuzzy inference approach can be improved to a significant extent by the method of compiling all rules off-line and saving fuzzy relations in array form for future consultation.

4.6 The Concluding Remarks

The main concern of this chapter is how to calculate the system reliability if the device reliability data are vague and imprecise as they were estimated subjectively.

Section 4.2 briefly reviewed the current approaches in applying FST to the subject of reliability evaluation. An intuitive explanation has been given in order to avoid unnecessary formalism. In section 4.3, Some fuzzy reliability combination operators are defined based on the concepts of fuzzy arithmetic. Based on them fuzzy reliability and failure possibility, as well as some fuzzy reliability index are defined which can be regarded as the extension of the classical probabilistic reliability in a fuzzy system. It is understood that fuzzy arithmetic based system reliability evaluation method has the merit on its computing efficiency, since what to be processed are a few parameters of a fuzzy reliability data.

The proposed fuzzy rule-based system reliability evaluation model has been described in section 4.4, where the knowledge of system reliability evaluation can be induced into fuzzy rules form. By using the possibility theory based fuzzy reasoning the reliability index at system level can be deducted. Techniques of device combination sequence control and different fuzzy connection matrix selection are presented. To illustrate how fuzzy system reliability evaluation model works, two cases are studied in section 4.5 and the results are discussed.

Chapter Five

Application Of Fuzzy Reliability Techniques To Power Generating System Analysis

5.1. Introduction

A basic element in power system planning is the determination of how much generating capacity is required to give a reasonable assurance of satisfying the future load requirement. This capacity should be capable of supplying the demand under conditions of generating unit forced outages and unforeseen variations in the system load requirements.

Significant steps forward in the use of probability methods for the assessment of power system reliability performance developed by Calabreas[13], Halperin and Adler[36]. Since then, a large number of reliability indices have been proposed and some of them have been taken into the practise in power system planning. A reliability index is defined broadly to be a quantity that measures and quantifies some aspect of system reliability performance. The various reliability indices used in the electrical power industry can generally be grouped into two broad categories-: (a) deterministic indices, which reflect postulated conditions; and (b) probabilistic indices, which consider the stochastic uncertainty inherent in power system operations. The school of probabilistic indices permit the quantitative evaluation of system alternatives by taking directly into consideration the parameters that influence reliability, such as the capacity of individual generation units and the forced outage rate of each unit.

To measure power system reliability performance adequately by any one of those probabilistic indexes, no matter whatsoever its consideration is on duration, frequency or the expectation , refer and get validity from the basic reliability indices such as Mean

Time To Failure (or failure rate), Mean Time To Repair (or repair rate) allocated to each individual unit. At the planning and design stage, however, these parameters of some units are insufficient or unavailable in terms of statistics under the certain circumstance. For example, a newly installed nuclear steam unit is perhaps without sufficient operation and test records to obtain any meaningful statistical conclusion. Besides, power system reliability analysis is to assessing the adequacy of existence of sufficient generation, transmission, and distribution facilities within the system to satisfying customer load demand. Therefore, forecasting the future load demand is a organic part of reliability analysis. However, the same problem is raised as to collect sufficient data to foresee the future demand. Because of the rapid change of the social and industrial patterns in modern time, it becomes more difficulty to forecast the future based on the past data.

The well-experienced human experts may remedy the defects of lack of statistic data to a certain degree, as a matter of fact the role of a human expert plays in judging the unit reliability has been recognised for long[4,29,37]. However, so far this subjective judgement has been forced to follow the axioms of probability theory which do not allow the tolerance on the value being given. Comparing the statement of " The occurrence of a hydro unit failure per year is 2 days " and the statement of "The occurrence of a hydro unit failure per year is more likely 2 days. It could be one day in some cases but anyhow won't be more than five days", which one of the above statement is more nature and easier for a human expert to express his judgmental knowledge? The answer is obvious.

While the traditional probability theory lost it merit on representing and handling this type of imprecise information, as a contrast, fuzzy set and possibility theory provide a unified mechanism to accommodate the human experts' judgmental knowledge. Zadel, the founder of the theory, has often expressed his belief in the pervasiveness and breadth of fuzziness such as:

"The pervasiveness of fuzziness derives from the fact that, in most of the classes of objects that we form in our perception of reality, the transition from membership to non membership is gradual rather than abrupt. This is true of the class of tall men, beautiful women, and larger numbers. And it is true of the meanings of such concepts as meaning,

intelligence ,truth, democracy, and love. In fact, the only domain of human knowledge in which non-fuzzy concepts play the dominant role is that of classical mathematics. On the one hand, this endows mathematics with a beauty, power, and universality unmatched by any other field. On the other hand, it severely restricts its applicability in fields in which fuzziness is pervasive---as is true, in particular, of humanistic systems, that is ,system in which human judgement, perception, and emotions play a central role. [95]"

Electric power system analysis, like any other physical systems analysis, has no exception lying more or less on human being's judgements. Therefore, based on the fact that in power system reliability analysis there are source information of which not only the randomness but also fuzziness encountered, we are able to amend the concept of fuzzy reliability into the area by considering both source data of generating capacity outage and load demand as fuzzy data.

In this chapter, it first reviews the basic concepts and techniques currently in use in the field of power generating system reliability analysis. Among varies reliability indices it is concentrating on the most widely used index LOLP. In the later section, fuzzy arithmetical reliability evaluation technique is amended to power generating system. For this purpose a fuzzy peak load model is proposed together with the possibility of capacity outage model, based on them a new index called Possibility of Load Loss (POLL) is defined. The proposed fuzzy power generating system reliability model is tested by using the practical RTS and the results obtained are analysed in section 5.4.

5.2. The Basic Concepts of Power Generating System Reliability

The term "reliability" as applied to power systems has a very wide range of meaning. These concerns can be divided into the two general categories:-(1) system adequacy; and (2) system security. System adequacy relates to the existence of sufficient energy to supply customs. It is associated with static system conditions without consideration of any system disturbance. System security, on the other hand, relates to the ability of the system to respond to disturbance arising within the system. The system reliability as it discusses here is only refer to system adequacy.

In power system studies, the time period is generally divided into two periods: one concerned with planning(long-term period) and the other concerned with operation(short-term period). In reliability evaluation of generating capacity the same subdivision is made. Although the method of analysis is different in the two time periods, the basic question is the same: "How much generating capacity is excess of the expected load level (reserve capacity) is required in order that the risk if not meeting this load is less than an acceptable value?". The term "generating system reliability evaluation" is usually defined as that the total system generation is examined to determine its adequacy to meet the total system load requirement. The generating system reliability model is shown in figure 5.1.

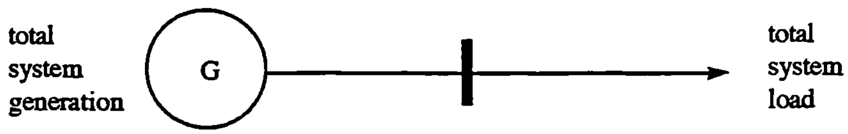


Figure 5.1 Generating System Reliability Evaluation Model

Power generating system is a sub-system of power system. When evaluating the reliability of generating System, it is generally assumed that the other parts of power system (transmission system, distribution system) are reliable, that is, if generating capacity are sufficient to meet the load, transmission and distribution system can transmit electricity to any load site, and would not cause shortage of electricity due to over load or bus-bar voltage beyond the limitation. Therefore, at any time, the measurement of system in normal operation or failure is that whether generating capacity can meet the demand of the forecast load. To improve generating system performance, or in another word to increase the reliability of a generating system, They are two ways to achieve it:-(1) increase the availability of the generating units; or (2) enlarge the generating reserve capacity. Obviously, the concept of reliability is closely associated with the reserve.

Similarly, reliability is also associated with the cost of installation and operation of the added units. So far there has no simple equation among them yet.

5.2.1. Generating Capacity Model

Generating capacity model has two parameters: unit size(generating capacity) and unit forced outage rate (FOR).

Out of the most important parameters is the forced outage rate---which is the probability of finding the unit on forced outage at some distant time in the future. Mathematically it is defined as unavailability given in table 2.1, chapter 2 as

$$\text{Unavailability(FOR)} = \frac{\lambda}{\lambda + \gamma} \qquad \text{eqn 5.1}$$

A FOR does not include any concepts of frequency and duration. For instance, if the failure rate and repair rate are doubled, FOR remains unchanged. Although techniques are available to account for frequency and duration of generating states, the most widely used and accepted technique for evaluating generating capacity reliability is based only on the concept of FOR.

The fundamental basis for evaluating the reliability of generating systems is the capacity outage probability table. As the name suggests, it is a simple array of capacity levels and the associated probabilities of existence. A typical outage probability table is evaluated using the binomial distribution, i.e., it considers the unit only has two states: in service and outage. The best method of deducing the capacity outage probability table is recursive technique, i.e., starting with the smallest unit, one unit is added to the table at a time until all units have been processed. Because of the discrete nature of the capacity outage states it is found that a very large system will lead to very intensive computing by using the well-known recursive techniques. Alternative model-building techniques were proposed attempting to improve the computing efficiency[9], among them the continuous normal distribution model and the Fourier transform model are two examples. The aim is to obtain a single entry in the table using only a few parameters which are derived from units size, FOR and the number of units in a system. However, it is found that the continuous model is not sufficiently accurate when compared to those obtained using the recursive technique. On the other hand, the Fourier transform model improves the accuracy only when the system is large enough. In this chapter it is the recursive technique being adopted.

The capacity outage probability table usually accounts on both individual and cumulative probability. The cumulative probability table has several advantages over the individual probability table, whereas the individual probability table indicates the probability of a certain outage capacity state, the cumulative probability corresponding to this value indicates the probability of this outage capacity or greater. Consequently, the probability of zero capacity or greater being out of service is unity. Besides, the value of expectation, say LOLP, will be no difference by using either individual or cumulative probability tables.

In practice, the available system capacities are not constants as units are added to or removed from system for keeping risk level remained or for periodic inspection and maintenance. A single capacity outage probability table is therefore not applicable if the system becomes larger and consists many units, it is impractical to completely rebuild the table each time a unit is to be added or removed. The basic system capacity outage probability (and cumulative probability) table can be modified directly and a new table developed. Such process can be done through following equation

$$P_n(x) = P_{n-1}(x)(1-q) + P_n(x-c)\,q \qquad \text{eqn 5.2}$$

Where $P_n(x)$ is the probability of an outage capacity equal to or exceeding capacity x after adding the unit of capacity c with outage probability q, and $P_{n-1}(x)$ is the probability of outage capacity equal to or exceeding capacity x before adding the unit. Using this equation, assume the first unit has P(0)=p, P(c)=q and p(x-c)=0 if x<c. To have cumulative probability table , assume the first unit has P(0)=1, P(c)=q and P(x-c)=1 if x<c.

To illustrate how a capacity outage probability table is obtained by using eqn 5.2, consider a subsystem of RTS which consists three 100MW fossil steam units and two 50MW Hydro units. Their FOR are given as 0.04 and 0.01 respectively (see appendix II). The calculated capacity outage probability table are listed in table 5.1.

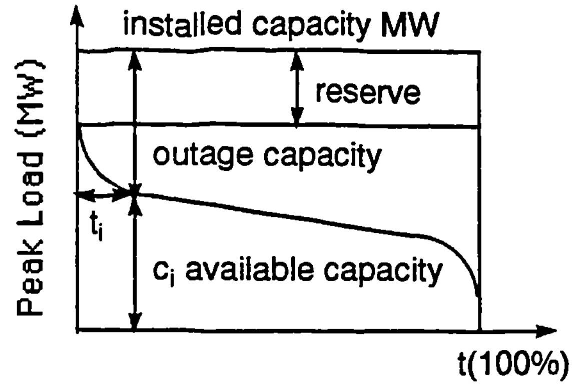
Capacity Out	Capacity In	Individual Probability	Cumulative Probability
0	400	0.867130	1.000000
50	350	0.17518	0.132870
100	300	0.108480	0.115352
150	250	0.002190	0.006872
200	200	0.004527	0.004682
250	150	0.000091	0.000155
300	100	0.000063	0.000064
350	50	0.000001	0.000001
400	0	0.000000	0.000000

Table 5.1 The Capacity Outage Probability Table of A Sample System

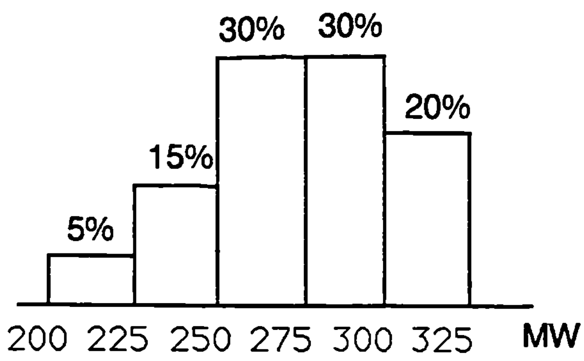
5.2.2. Load Model

In last section a capacity outage probability table is used to evaluate the probabilistic risk assuming a constant load level. In practice, however, load vary and therefore a load model as well as a generation model is required for system reliability assessment.

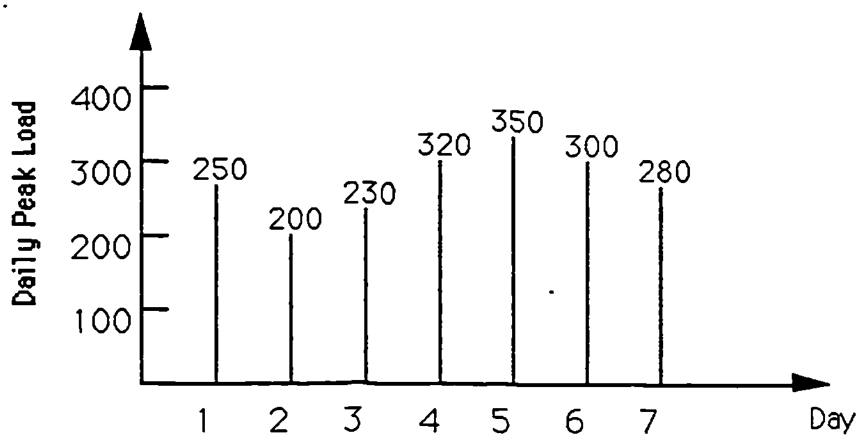
The load models which are currently in use are three types:-(1) The simplest and quite extensively used model is daily peak load model in which each day is represented by its daily peak load; (2) The individual daily peak loads can be arranged in descending order to form a daily peak load probability distribution; and (3) a cumulative peak load probability distribution is known as the peak load duration curve. Three typical load



Peak Load Duration Curve



Daily Peak Load Probability Distribution



Daily Peak Load

Figure 5.2 Three Typical Types of Load Models

---

models are illustrated in figure 5.2. All the load models are based on the assumption that daily peak load last whole day.

Choosing a possible load model convoluted with the generating capacity model will result a possible system risk index. For instance, the units are in days if the daily peak load variation curve is used and in hours if the load duration curve is used. In Reliability Test System (see appendix II), the annual peak load is suggested as 2850 MW. Three tables of load data are given on weekly, daily and hourly peak load in percent of the annual, weekly and daily peak respectively.

5.2.3 Review of techniques for reserve capacity

The estimation of the reserve of generating capacity is an important task for whatsoever power system planning, design and operation[33]. This section mainly discusses the popular approaches to estimate generating capacity reserve. The techniques currently in use to estimate reserve capacity are six types as following:

- Percentage reserve margin method
- Largest unit reserve method
- Loss of load probability (LOLP) method
- Frequency and duration (F&D) method
- Loss of energy probability (LOEF) method
- Loss of load expectation (LOLE) method

The first two methods are deterministic criteria methods and the remainder are probabilistic methods. They are briefly discussed here in turn. In the next section, the loss of load probability (LOLP) method will be discussed in detail.

5.2.3.1 Non-probabilistic Methods

<u>Percentage Reserve Margin Method</u>

The most common "rule-of-thumb" of non-probabilistic methods are percentage reserve margin, a reserve equal to the largest unit or a combination of both. Percentage reserve margin requires the system reserve capacity being a fixed percentage (e.g., 20-25%) of system peak load of a year. This method can not account for difference in system size and system load characteristics (load sharp, load forecast uncertainty) nor can they account for the impact of different sizes (FOR, maintenance schedule etc.) and types of generating units. Consequently, two systems having the same percentage reserve or a reserve equal to the largest unit, can have vastly different probabilistic risks, that is, probability of not meeting the load. To illustrate this using the system given in table 5.1, assume that the expected load demand is 300 MW, the installed capacity is such that there is a 25% reserve margin, then the cumulative probability of not meeting the load from table 5.1 is obtained as

$$P(\text{capacity out} \geq \text{reserve})=0.115352$$

Largest Unit Reserve Method

Largest unit reserve method has the same shortage as the percentage reserve method. It requires the reserve equal to the largest unit in the system. For illustration, the example is still used. Assuming that the expected load demand is 300 MW, the largest unit in the system is 100 MW fossil steam unit, the cumulative probability of not meeting the load is

$$P(\text{capacity out} \geq \text{reserve})=0.115352$$

5.2.3.2 Probabilistic Methods

Loss of Load Probability Method

LOLP method is developed based on the approach of using probability theory to determine the reserve capacity , which was first introduced in power system reliability evaluation by Calabress in 1947. This method has considered the impact of unit size, load size and maintenance schedule. Actually, LOLP index is the value of expectation, that is , if for a certain system it has LOLP as 0.1d/a, it indicates that there should has the expected 0.1 day (2.4 hour) load loss in a year due to shortage of generating capacity from the probability of mean.

The advantage of LOLP method are easy calculation, clear physical meaning. However, it can not reflect the daily load change, nor the number of times and duration of load lose.

Frequency and Duration Method

F&D method was introduced in power system reliability evaluation by Halpering and Adler in 1958 , and developed by Ringlee and Wood (1966). It identifies the expected frequency of encountering a deficiency and the expected duration of the deficiencies. It therefore contains additional physical characteristics which makes it sensitive to further parameters of the generating system, and so it provides more information to power system planners. The index has not been used very widely in generating system reliability analysis, partly for the reason that it requires more source data and its calculation is more complicated in comparison with LOLP method.

Loss of Energy Probability Method

LOEP method was given by AIEE in 1960. LOEP equals to the ratio of electrical energy loss due to load loss and total energy to meet the load.

Loss of Load Expectation Method

LOLE method is the extension of LOLP method. It has the number of days of load loss in a certain period(usually a year) due to the shortage of electricity supply as a index.

In general, all of these four methods described above are based on the criterion of generating capacity meet the demand of load. Therefore, each method requires two models: (1) a generating capacity model; and (2) a forecast peak load model. The applicable system capacity outage probability table is combined with the system load characteristic to give an expected risk of loss of load, which is the aim of generating system reliability analysis.

The above described indices are generally calculated using direct analytical techniques. Analytical techniques represent the system by a mathematical model and evaluate the reliability indices from this model using mathematical solutions. A conceptual analytical model for evaluating power generating system adequacy indices is shown in figure 5.3.

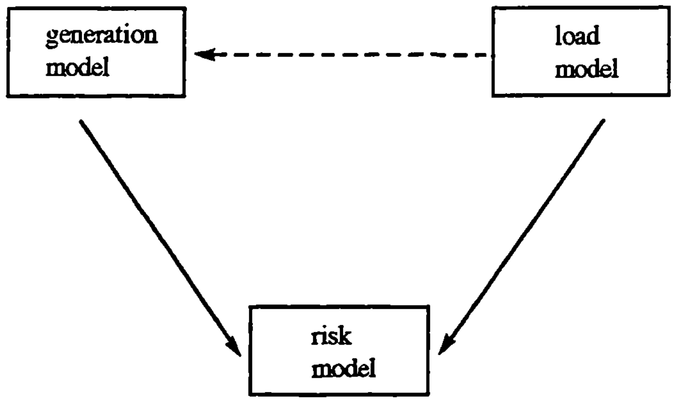


Figure 5.3 Conceptual Tasks For Generating System Reliability Evaluation

5.2.4 Widely Used LOLP Approach

The loss of load probability is the most widely accepted and used probabilistic method for evaluating the risk level in generation system. Its definition is presented in last section. The time units are in days or hours depending upon the load characteristic used.

Prior to combining the outage probability table it should be pointed out that there is a difference between the terms "capacity outage" and "loss of load". The term "capacity outage" indicates a loss of generation which may or may not result in a loss of load. This condition depends on the generating capacity reserve margin and the system load level. A "loss of load" will occur only when the capacity of the generating capacity remaining in service is exceeded by the system load level.

A particular capacity outage will contribute to the system expected load level by an amount to the product of the probability of existence of the particular outage and the number of time units in the study interval that loss of load would occur if such a capacity outage were to exist. It can be seen from the peak load duration curve of Fig. 5.1 that any capacity outage less than the reserve will not contribute to the system expected load loss.

Outages of capacity in excess of the reserve will result in varying numbers of time units during which load loss could occur. Expressed mathematically, the contribution to the system loss of load made by capacity outage q_i is $p_i t_i$ time units. The total expected load loss for the study interval is given as

$$\text{Loss Of Load Probability} = E(t) = \sum_{i=1}^{n} p(C < L_i) t_i \qquad \text{eqn 5.3}$$

where C is the capacity in service and L_i is the peak load at time i. To illustrate this, consider the system presented in table 5.1, and assume the system load has its characteristics as individual daily peak load shown in figure 5.2, then

$$\begin{aligned} LOLP &= \sum_{i=1}^{7} p_i(\text{capacity in} < \text{peak load}) t_i \\ &= (0.004682 + 0.000155 + 0.004682 + 0.115352 + 0.115352 + 0.006872 + 0.006872) \\ &= 0.253967 \quad \text{days / week} \end{aligned}$$

Suppose in a year the system configuration and load characteristic remain unchanged, therefore, the annual (364 days) loss of load risk level is

$$LOLP = 52 \times 0.253967 = 13.21 \text{ days/ year}$$

Although LOLP approach shows its advantage for evaluating generating system reliability, it shall indicate that in practice it may need to combine two or more probabilistic method to evaluate a certain complicated system.

5.3 Fuzzy Generating System Reliability Evaluation

Similar as in probabilistic power generating system analysis, the aim of fuzzy generating system reliability evaluation is that to measure the adequate of sufficient generating capacity to satisfying the load demand. The difference between two approaches lies on the fact that in fuzzy generating reliability framework the units reliability data and the load level are seen as fuzzy data. Hence, in a fuzzy generating system reliability model the tasks are to construct fuzzy outage capacity model and fuzzy load model, then combine these two models in order to determine the risk criterion.

5.3.1 Fuzzy Outage Capacity Model

It has been recognised that there are common situations in power system reliability analysis that some, or all of units of a system whose failure and repair information are statistically insufficient or unavailable and hence it has to depend upon human expert's subjective judgement. These information then are not only encountering sole randomness but also fuzziness, for human being's judgement are fuzziness in natural as Zadel emphasised. Therefore, the forced outage rate is a fuzzy data for it is determined by the subjectively obtained failure and repair information. The fuzzy FOR is the fuzzy unavailability given in eqn 4.21, where FOR is represented as a triangular fuzzy number $TFN_{FOR}(x; a, b, c)$.

To calculate the possibility of outage capacity, Similarly as in the probability case, eqn 5.2 in section 5.2.1 is used to calculate the possibility of outage capacity. The eqn 5.2 is extended into the possibility distribution in the way as following: let fuzzy FOR for a unit be represented as a triplet $TFN_{FOR}(a, b, c)$ and C is the capacity of this unit; let the current possibility of outage capacity be $TFN_{n-1}(a_{n-1}, b_{n-1}, c_{n-1})$. Then, instead of calculating the possibility of outage capacity directly, it is to calculate their three parameters a, b, c and $a_{n-1}, b_{n-1}, c_{n-1}$. The possibility of outage capacity after added a new unit is given as

The possibility of outage capacity $=TFN_n(x; a_n(x), b_n(x), c_n(x))$ eqn 5.4

where

$$\begin{aligned} a_n(x) &= a_{n-1}(x) \times (1-c) + a_{n-1}(x-C) \times a \\ b_n(x) &= b_{n-1}(x) \times (1-b) + b_{n-1}(x-C) \times b \\ c_n(x) &= c_{n-1}(x) \times (1-a) + c_{n-1}(x-C) \times c \end{aligned} \qquad \text{eqn 5.5}$$

where $TFN_n(x)$ is the possibility of an outage equal to or exceeding a capacity state x after adding a capacity C unit with an outage possibility $TFN_{FOR}(a, b, c)$, and $T_{n-1}(x)$ is the possibility of outage equal to or exceeding a capacity state x before adding the unit. Similarly, for the first unit being added it is assumed

$TFN(x=0) = TFN(x; 1, 1, 1)$

$TFN(x=C) = TFN_{FOR}(x; a, b, c)$

$TFN(x=x-C)=TFN(x; 1, 1, 1)$ if $x<C$ eqn 5.5'

That is, three parameters a, b, and c are cumulated. Further assumption are made on the parameters a,b,c, for the situation that if they are greater than 1.0 then these parameters are assigned as 1.0. Hence, similar to the capacity outage probability table, we are able to construct the capacity outage possibility table where the single crisp probability is replaced by the fuzzy number on the unit space.

5.3.2 Fuzzy Load Model

Since the determination of peak load in a certain duration is an extremely difficult task, and human experts' judgmental knowledge are the favourable aid to the load forecasting, the load model are determined more or less subjectively as well as the capacity model. That is, similar as previous definition of fuzzy data for the capacity model, fuzzy peak load can be expressed as the vague statements such like " daily peak load is more likely around 150 MW. It should be no less than 120 MW and not exceed 200 MW". Such expression can be modelled as a TFN. Let y be the variable on the universe of discourse Y, where Y is the peak load level, and also let TFN_{load} be represented by triplet (a, b, c), then the possibility of the peak load at a time interval can be defined as

Peak Load=$TFN_{load}(y; a,b, c)$ eqn 5.6

To determine a generating system risk level it demands to combine both fuzzy capacity outage model and fuzzy load model. In a fuzzy capacity model all the possible outage states are listed in the form of a discrete series. Hence, the estimated fuzzy peak load has to be discrete in accordance with the capacity outage model so that the process of combination can be carried out. The process of discreting considers two possible situations:-(1) at least one capacity state of an outage capacity model is within the boundary of a load capacity distribution. In this case it is simply to calculate the grade of membership of the corresponding load capacity using eqn 4.2; (2) none of the capacity state is within the boundary of a load capacity distribution. In such case it can use the fuzzification technique which is described in chapter 6. Briefly, if there has a fuzzy load estimation $TFN_{load}(y;a,b,c)$ and there are two possible capacity states C1 and C2 which are next to a and c. The grade of membership of load level at C1 and C2 can be obtained as

$$\mu_{load}(C1) = \frac{b - C1}{C2 - C1}; \qquad \mu_{load}(C2) = \frac{C2 - b}{C2 - C1} \qquad \text{eqn 5.7}$$

The time interval of fuzzy peak load could be a year, a season, a week, a day or an hour, depending on which type of load models is preferred. However, by applying the extension principle and the derived operators which were given in chapter 4, a fuzzy peak load at a time interval can be translated to any other intervals.

5.3.3 Possibility Of Load Loss (POLL) As A Possibilistic Index

Based on the fuzzy capacity outage model and fuzzy load model given in the last section, it is able to define a new reliability index called " Possibility Of Load Loss". Indeed this new index is the extension of LOLP, of which the probability of reserve capacity less than peak load is in a interval where each probability has a value π, $\pi \in [0,1]$ associated. π is the degree of possibility. POLL is defined as

$$\begin{aligned} \text{POLL} &= \sum_{i}^{n} \text{TFN}(P[\text{capacity out} \supseteq \text{reserve}];a_i,b_i,c_i) \\ &= \sum_{i}^{n} \text{TFN}(P[\text{capacity in} \subset \text{peak load}];a_i,b_i,c_i) \end{aligned} \qquad \text{eqn 5.8}$$

where $\subset$ means fuzzy containment, since both capacity out and peak load are fuzzy event. The operation of fuzzy containment is to measure the degree of a fuzzy data

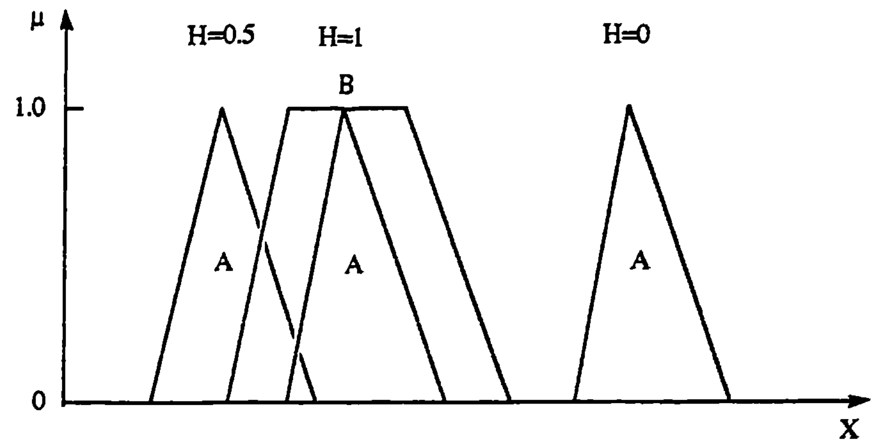


Figure 5.4 Demonstration of Fuzzy Containment Operation

containing another fuzzy data (see figure 5.4). If A and B are two fuzzy numbers, the degree of A contained in B can be calculated

$$H = \frac{\int \mu_A(x)\mu_B(x)dx}{\int \mu_A(x)dx} \qquad \text{eqn 5.9}$$

or if A and B are discrete fuzzy numbers, then

$$H = \frac{\sum_{i=0}^{n} \mu_A(x_i)\mu_B(x_i)}{\sum_{i=0}^{n} \mu_A(x_i)} \qquad \text{eqn 5.10}$$

5.3.4 Algorithm For Calculating POLL

To calculate POLL, let X be the universe of discourse of capacity in service probability, Y be the universe of discourse of possible capacity in service state. TFN(x; a_i, b_i, c_i) is the possibility of the ith capacity in service and $\mu(y_i)$ is the grade of membership of a load level at y_i. It is known that the operations on TFNs yield a TFN. Therefore, Possibility Of Load Loss can be determined as

$$POLL = TFN_{POLL}(x; a^*, b^*, c^*) \qquad \text{eqn 5.11}$$

where

$$a^* = \frac{\sum_{i=0}^{n} a_i \mu(y_i)}{\sum_{i=0}^{n} \mu(y_i)}$$

$$b^* = \frac{\sum_{i=0}^{n} b_i \mu(y_i)}{\sum_{i=0}^{n} \mu(y_i)}$$

$$c^* = \frac{\sum_{i=0}^{n} c_i \mu(y_i)}{\sum_{i=0}^{n} \mu(y_i)} \qquad \text{eqn 5.12}$$

The algorithm of combining fuzzy capacity model and fuzzy load model to give a possible risk level of load loss is demonstrated graphically in figure 5.6. The detailed explanation is also given in the next section, where a numerical example of a RTS subsystem is employed.

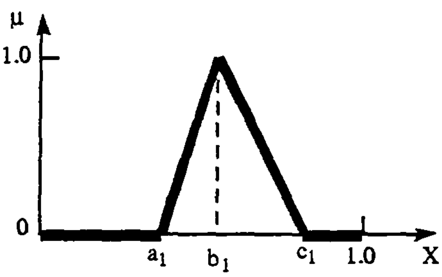
5.4 Case Studies

Two case studies are conducted in this section. The first case is to study a small system reliability in which 5 units are connected together to produce the total capacity of 400 MW. The aim of this case study is to demonstrate how the proposed fuzzy power generating system reliability model works in detail. In the second case the practical Reliability Test System (RTS) which consist 32 units is tested by the proposed method.

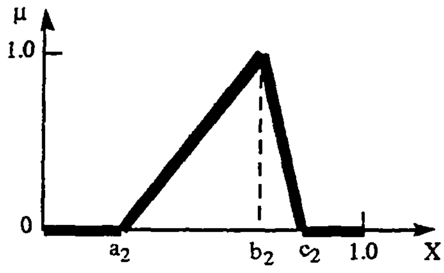
5.4.1 Case I

A subsystem of RTS which consists three 100 MW fossil units and two 50 MW hydro units is selected for study. The large capacity fossil units are for the base load and the small capacity units are for the peak load. The estimate of MTTR and MTTF for both type of units are given in appendix II. Based on these information the units FOR can be calculated.

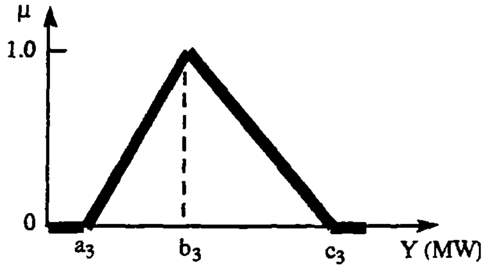
Unit 1: C_1; $TFN_{FOR}(x, a_1, b_1, c_1)$



Unit 2: C_2; $TFN_{FOR}(x, a_2, b_2, c_2)$



Peak load: $TFN_{Load}(y, a_3, b_3, c_3)$



By using eqn.5.4, eqn.5.5

	Capacity in service	Possibility
i=1	0	$TFN(x;\ a_0, b_0, c_0)$
i=2	C_1	$TFN(x; a_{C1}, b_{C1}, c_{C1})$
i=3	C_2	$TFN(x;\ a_{C2}, b_{C2}, c_{C2})$
i=4	C_{1+2}	$TFN(x;\ a_{C1+C2}, b_{C1+C2}, c_{C1+C2})$

By using eqn.4.2, eqn.5.7

$\mu(y_i) = [\mu(0),\ \mu(C_1),\ \mu(C_2),\ \mu(C_1+C_2)]$

By using eqn.5.12, eqn.5.11

$$a^* = \frac{\mu(0) \times a_0 + \ldots\ldots + \mu(C_1+C_2) \times a_{C1+C2}}{\mu(0) + \ldots\ldots + \mu(C_1+C_2)}$$

$$b^* = \frac{\mu(0) \times b_0 + \ldots\ldots + \mu(C_1+C_2) \times b_{C1+C2}}{\mu(0) + \ldots\ldots + \mu(C_1+C_2)}$$

$$c^* = \frac{\mu(0) \times c_0 + \ldots\ldots + \mu(C_1+C_2) \times c_{C1+C2}}{\mu(0) + \ldots\ldots + \mu(C_1+C_2)}$$

Possibility of load loss = $TFN(x;\ a^*, b^*, c^*)$

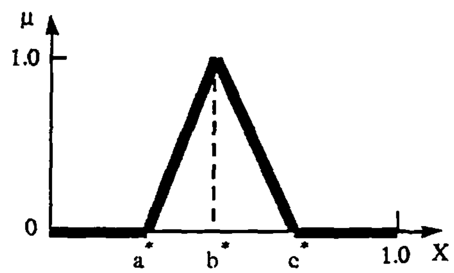


Figure 5.5 Algorithm of Possibility Of Load Loss Index Calculation

If there is the situation that a human expert expressed his judgement on units failure and repair information in a way like " the given estimate for both type of units should allow a small divergence", and if ' small' be interpreted as 10% divergence, then the units failure and repair information can be modelled as fuzzy numbers. The units outage information thus obtained will be

50 MW unit: $TFN_{MTTR}(h;18,20,22)$ $TFN_{MTTF}(h;1782,1980,2178)$

100 MW unit: $TFN_{MTTR}(h;45,50,55)$ $TFN_{MTTF}(h;1080,1200,1320)$

the forced outage rate for 50 MW units:

$$
\begin{aligned}
TFN_{FOR}(x;a,b,c) &= \frac{TFN_{MTTR}(h;18,20,22)}{TFN_{MTTF}(h;1782,1980,2178) + TFN_{MTTR}(h;18,20,22)} \\
&= TFN_{FOR}(x;\frac{18}{2178+22};\frac{20}{1980+20};\frac{22}{1782+18}) \\
&= TFN_{FOR}(x;0.0082,0.0100,0.0122)
\end{aligned}
$$

the forced outage rate for 100 MW units:

$$
\begin{aligned}
TFN_{FOR}(x;a,b,c) &= \frac{TFN_{MTTR}(h;45,50,55)}{TFN_{MTTF}(h;1080,1200,1320) + TFN_{MTTR}(h;45,50,55)} \\
&= TFN_{FOR}(x;\frac{45}{1320+55};\frac{50}{1200+50};\frac{55}{1080+45}) \\
&= TFN_{FOR}(x;0.0327,0.0400,0.0489)
\end{aligned}
$$

To construct the fuzzy capacity model, consider first that a 50 MW unit being added to the empty table. Two capacity outage states are: 0 MW and 50 MW. According to eqn 5.5', the possibility of capacity outage for above two states are obtained as

$TFN_{y=0}(x; 1,1,1)$; and $TFN_{y=50}(x; 0.0082, 0.0100, 0.0122)$

add each unit in the system in turn by using eqn 5.4 and eqn 5.5, the capacity outage possibility table is obtained as shown in table 5.2. In this table the three parameters are truncated at a cumulative probability of 10^{-8}. The system has 9 states.

The load model used is individual daily peak load listed in figure 5.2. To calculate POLL, three cases are suggested as:

Capacity Out	Capacity In	Possibility
0	400	TFN(x; 0.944586, 1.000000, 1.000000)
50	350	TFN(x; 0.105094, 0.132870, 0.167535)
100	300	TFN(x; 0.091156, 0.115352, 0.145632)
150	250	TFN(x; 0.004510, 0.006872, 0.010476)
200	200	TFN(x; 0.003072, 0.004682, 0.007154)
250	150	TFN(x; 0.000083, 0.000155, 0.000287)
300	100	TFN(x; 0.000034, 0.000064, 0.000119)
350	50	TFN(x; 0.000000, 0.000001, 0.000003)
400	0	TFN(x; 0.000000, 0.000000, 0.000000)

Table 5.2 A Capacity Outage Possibility Table For Case I Study

---

(a) 10% fuzziness of MTTR and MTTF estimation of all the units; 10% fuzziness of all daily peak load estimation.

(b) 10% fuzziness of MTTR and MTTF estimation of all the units; 30% fuzziness of all daily peak load estimation

(c) no fuzziness about MTTR and MTTF estimation of all the units; 30% fuzziness of all daily peak load estimation.

The possibility distribution of daily peak load can be derived. For day one it has fuzzy peak load estimation TFN(y; 225, 250, 275), It is mapped to a finite discrete set Y=[0, 50, 100, 150, 200, 250, 300, 350, 400] MW as

(a) $\mu(y)$ = [0.00,0.00,0.00,0.00,0.00,1.00,0.00,0.00,0.00]

(b) $\mu(y)$ = [0.00,0.00,0.00,0.00,0.33,1.00,0.33,0.00,0.00]

(c) $\mu(y)$ = [0.00,0.00,0.00,0.00,0.33,1.00,0.33,0.00,0.00]

The possibility of load loss for day one can be calculated as

For case (b)

$$a^* = \frac{0 \times 0 + \ldots + 0.003072 \times 0.33 + 0.004510 \times 1.0 + 0.091156 \times 0.33 + \ldots + 0.944586 \times 0}{0 + \ldots + 0.33 + 1 + 0.33 + \ldots + 0}$$
$$= 0.021449$$
$$b^* = \frac{0 \times 0 + \ldots + 0.004682 \times 0.33 + 0.006872 \times 1.0 + 0.115352 \times 0.33 + \ldots + 0.944586 \times 0}{0 + \ldots + 0.33 + 1 + 0.33 + \ldots + 0}$$
$$= 0.0280019$$
$$c^* = \frac{0 \times 0 + \ldots + 0.007154 \times 0.33 + 0.010476 \times 1.0 + 0.145632 \times 0.33 + \ldots + 0.944586 \times 0}{0 + \ldots + 0.33 + 1 + 0.33 + \ldots + 0}$$
$$= 0.0366839$$

$POLL_{case}$ (b)=TFN(x; 0.021449, 0.0280019, 0.0366839) days/day

Similarly, for day one it has

$POLL_{case}$ (a)=TFN(x;0.004510, 0.006872, 0.010476) days/day

$POLL_{case}$ (c)=TFN(x;0.0280019, 0.0280019, 0.0280019) days/day

Among the above results, POLL for case (a) considered fuzziness in both capacity outage and peak load level. All three parameters are greater than 0.010476 which is the upper boundary of the probability of 150MW reserve capacity. This result is quite reasonable, since there has a degree of possibility (0.33) that the load level is higher at 300 MW, which has an associated higher probability. Such effect has been reflected in the result as the calculated value lies somewhere in between the probabilities of 150 MW and 100 MW reserve. POLL for case (b) only counted fuzziness in capacity outage, since the fuzziness of peak load has no effect on the result after it has been mapped to the finite capacity set. POLL for case (c) has a crisp output because of non-fuzzy capacity outage assumption. The result was weighted among three probabilities associated with possible load loss capacity states because of the fuzziness in peak load estimation.

A weekly POLL can also be obtained as the sum of the calculated daily POLL using the daily peak load model stated in figure 5.2.

5.4.2 Case II

The RTS system was developed in order to create a consistent and generally acceptable system and data set that could be used in both generating system and composite system reliability evaluation[73]. The RTS system consists of 32 units. The total installed capacity in this system is 3405 MW. The generation reliability data are given in table A2.1, appendix II, where 3 basic indices namely units MTTR, MTTF, scheduled maintenance together with the derived FOR are presented.

The load data are given in table A2.2 and A2.3, where they appear as the weekly and daily peak load as a percentage of annual and weekly peak respectively. The data in table A2.2 and A2.3 define a daily peak load model of 364 days with Monday as the first day of the year. The suggested system peak load is 2850 MW. The system reserve can be determined as 555 MW.

The conventional risk evaluation model was first programmed. The program contains three subroutines:-(1) capacity outage table calculation; (2) the daily peak load table calculation; (3) risk evaluation program. The exact state capacity table was generated where the cumulative probability was truncated at 10^{-6}. It was found from the table that the cumulative probability of 556 MW capacity outage is 0.084578. Hence, the LOLP for the peak day (On Tuesday of 51th week of the year) was determined as 0.084578 days/day. By the sum of 364 LOLP for each day in the year it is obtained that the loss of load probability for the year is 1.36886 days/year.

The program was later converted to accommodate and process fuzzy data by replacing single probability and load variable with three parameter variables. Using the fuzzy generating system risk evaluation program it first created the system capacity in service possibility table. Some of representative capacity states are shown in table 5.3.

To evaluate the RTS system risk level under fuzzy environment, three cases are suggested as

(A). All the generation unit reliability data has 10% fuzziness; 364 daily peak load data has no fuzziness.

(B). All the generation unit reliability data has 10% fuzziness, 364 daily peak load has 5% fuzziness.

Capacity Out	Capacity In	Possibility = TFN(x; a, b, c)
0	3405	(0.937954, 1.000000, 1.000000)
12	3393	(0.710916, 0.763605, 0.832965)
20	3385	(0.681803, 0.739483, 0.805297)
24	3381	(0.576531, 0.634418, 0.694688)
40	3365	(0.403343, 0.433434, 0.474830)
100	3305	(0.486527, 0.547601, 0.613325)
120	3285	(0.458972, 0.512059, 0.564659)
160	3245	(0.409415, 0.450812, 0.518734)
265	3140	(0.272251, 0.335567, 0.390144)
400	3005	(0.208705, 0.261873, 0.331104)
500	2905	(0.072369, 0.122516, 0.189772)
556	2894	(0.036779, 0.084578, 0.145596)
600	2850	(0.025894, 0.062113, 0.118830)
650	2755	(0.009759, 0.049419, 0.089925)
700	2705	(0.007874, 0.042461, 0.082231)
750	2655	(0.007011, 0.038471, 0.079652)
800	2605	(0.006133, 0.024719, 0.066318)
850	2555	(0.005846, 0.014731, 0.052590)
900	2505	(0.005225, 0.011608, 0.050012)
950	2455	(0.003051, 0.007492, 0.009235)
1000	2405	(0.001874, 0.004341, 0.007266)
1100	2305	(0.000938, 0.002353, 0.005115)
1200	2205	(0.000498, 0.000791, 0.001103)
1300	2105	(0.000204, 0.000401, 0.000782)
1400	2005	(0.000087, 0.000102, 0.000428)
1500	1905	(0.000019, 0.000040, 0.000071)
1600	1805	(0.000000, 0.000001, 0.000039)

Table 5.3 Some of Representative RTS Capacity Outage Possibility Data

Case (A) result

The possibility of load loss for the peak day is obtained as

$$\text{POLL} = \text{TFN}(x; 0.0367794, 0.084578, 0.145596) \quad \text{days / day}$$

$$= \begin{cases} 0 & \text{if } x > 0.145596 \text{ or } x < 0.0367794 \\ \dfrac{x - 0.036779}{0.084578 - 0.036779} & \text{if } 0.036779 \leq x < 0.084578 \\ \dfrac{x - 0.145596}{0.084578 - 0.145596} & \text{if } 0.145596 \leq x < 0.084578 \end{cases}$$

By the sum of 364 POLL it obtains the annual POLL as

POLL=TFN(x; 1.296654, 1.368861, 1.450095) days/ year

<u>Case (B) result</u>

The possibility of load loss for the peak day is calculated as

POLL=TFN(x; 0.089841, 0.095920, 0.102762) days/day

By the sum of 364 POLL it has

POLL=TFN(x; 1.353442, 1.5385998, 1.690034) days/ year

From the obtained results it has found that:-(1) in case (A) the calculated the peak day and the annual POLL has the value of its centre parameter as the same of the value calculated by the conventional method where only single crisp probability is counted. This is due to the assumption of non-fuzzy load data. The fuzziness of the generation units failure and repair data are represented in the form of triangular fuzzy number in the result, in which each probability within the boundary has an associated possibility value, e.g., a probability of 0.06 has an associated possibility as 0.49, which can be interpreted as there has 0.49 degree to believe that the loss of load probability is 0.06 days/day is true; (2) in case (B) the calculated results has reflected the inherent fuzziness in the load data. Comparing the calculated POLL with the POLL in case (A) it found that the POLL in case (B) is larger than the POLL in case (A). It is because in the later case the fuzziness of load data has been considered. The peak load at 2950 MW has the possibility of 0.30. At this capacity state it has a large probability of load loss. The fuzzy generating system reliability model has counted in such effect and reflected this possibility in the result.

Therefore, the obtained results are quite convinced, and it concludes that the proposed model is valid.

5.5 The Concluding Remarks

Reliability evaluation is an important aspect of any power generating system. Although there are a number of techniques available, none of them considered the inherent fuzziness uncertainty in human experts' judgmental knowledge expression of reliability source data estimation. This chapter has described one particular technique based on the concept of fuzzy arithmetic, which is the one of important and core branches of FST.

In this chapter the fuzzy reliability model has been emerged into electrical power generating system evaluation in order to determine the risk criterion under the fuzzy environment, based on the assumption that the statistical information of both generation units reliability and peak load are insufficient or unavailable.

The fuzzy capacity outage model and fuzzy peak load has been constructed, which can accommodate various vague statements and process these fuzzy data by modelling them as parametric fuzzy numbers. By convolution of these two models , a possibilistic index named "Possibility Of Load Loss" is determined. The fuzziness encountered in source information, which may be important to decision makers, will be kept and reflected in the final result. The supporting argument for using the new index is that the decision makers should have more options to make decisions with certain degree of confidence.

To test the validation of the proposed model, this approach was applied to the RTS system. The results demonstrated that the proposed model is the extension of the conventional model. The real merit of the proposed technique is that it can be used to determine the generating system risk level when some, or all of source data are fuzzy in nature, while the conventional model is incapable to handle this situation.

Chapter Six

Implementation of Fuzzy Rule-Based Expert System Shell(FRBESS) For Reliability Evaluation

6.1 Introduction

Attempts of using the currenlyt available fuzzy knowledge based shell systems for reliability prediction and calculation have failed. It was practically due to:-(1) There had no sufficient fuzzy inference systems available for trial when the research was conducted; (2) The only available system in the computer centre was REVEAL, and it had been off-loaded for a long time so that there was no support at all (e.g. introduction bulletin, user manual etc.). It came to no alternative but to develop a customised fuzzy knowledge based environment. This chapter outlines the fundamental structure of a fuzzy rule-based expert system shell called FRBESS which had been programmed. It also examines and discusses several key design issues of this system that are directly related to the implementation of the outlined reliability prediction and calculation framework in chapter 3 and chapter 4.

The first fuzzy inference system emerged was FUZZY by LeFaivre[52] in 1974. After ten year ICL developed REVEAL[39]. Since then some other systems have been reported include CADIAG, ARIES, SPHINX and SPII[1,55,28]. The list of fuzzy based knowledge system is by no means exhaustive. These systems have some successes in their application domains, due to their careful selection of fuzzy techniques and operations (such as definitions of linguistic variables, fuzzy operations and inference mechanism etc.). From a practical point of view, the implementation of FRBESS is particular relevant because it is important to learn how this fuzzy inference engine can be constructed in such a way to achieve maximum effectiveness so that the underlined fuzzy rules can be closely represented and hence be reasoned to their absolute meaning.

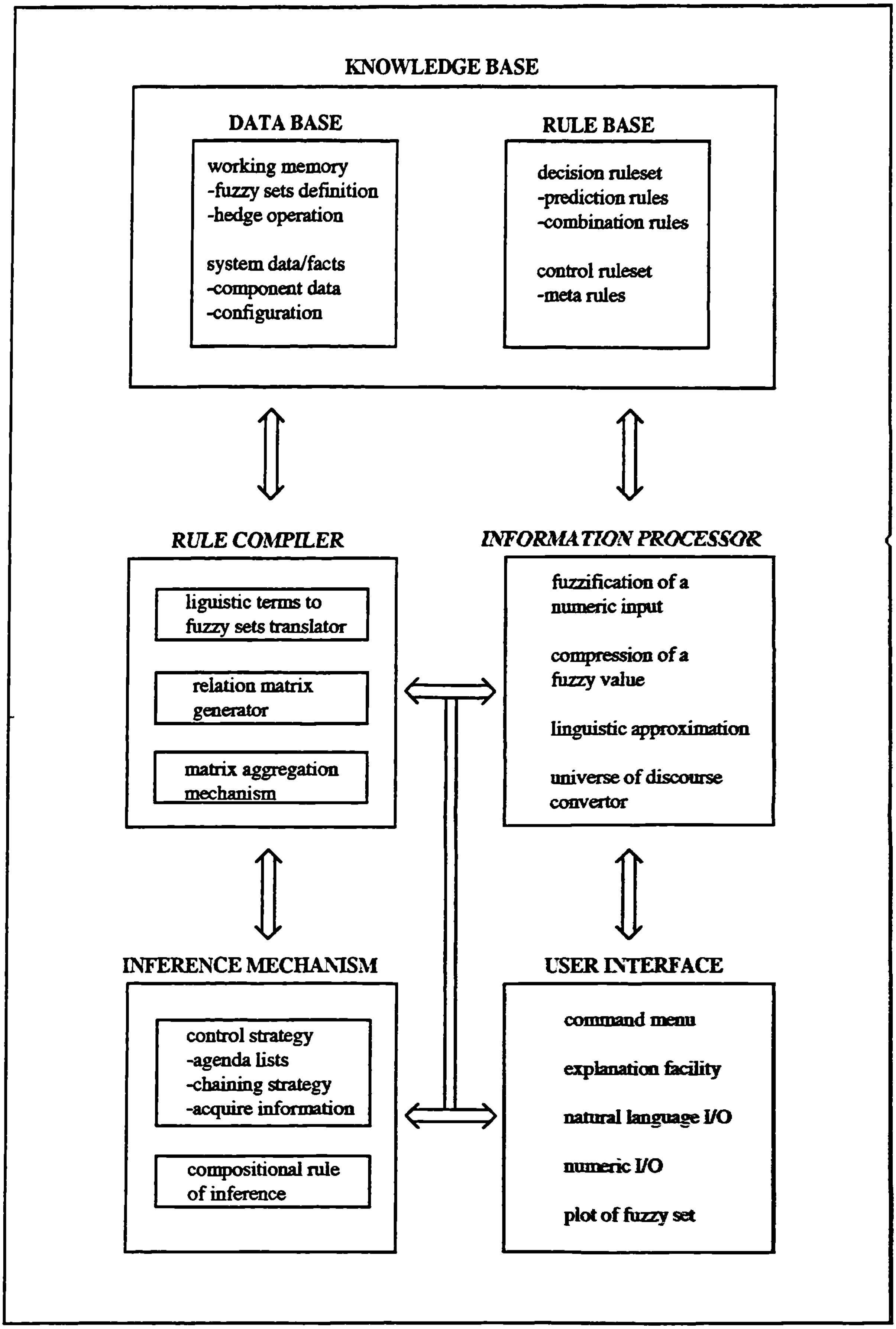


Figure 6.1 The Modules Structure of FRBESS

6.2 Fundamental Structure of FRBESS

The proposed skeletal frameworks presented in figure 3.1 and figure 4.4 have been elaborated in a specific details as far as implementation is concerned. Briefly, FRBESS consists of two files (knowledge base) and a main program (inference engine) that constantly interacts these two files, that is, the rule base and the data base. The outlined structure of FRBESS is presented in figure 6.1.

To apply the system to a problem, the knowledge engineer or the expert himself first designs his model. He then enters it into the knowledge base files in the computer by creating a file. If the knowledge engineer/expert also wants to use his own defined data(instead of using the default linguistic values), in this case he can input his own fuzzy terms and inference rules into the knowledge base. The system also allows the expert's to define their own inference control strategy by entering a set of meta control rules into the rule base under MACSYMA syntax. The input meta rules need to be compiled into LISP source code so that the system will control the reasoning sequence based on the user defined strategy rather than by default the depth-first forward reasoning strategy.

The inference engine consists of four main program modules. These modules are:- (1) a rule compiler; (2) an inference mechanism; (3) an information processor; and (4) an user friendly interface. The rule compiler first translate all linguistic terms embedded in rules into their associated fuzzy sets, according to the definition of fuzzy sets and hedge operation defined in the data base, then compile these fuzzy sets in a rule into a fuzzy relational matrix according to a chosen implication operator, and further aggregate these matrices of a ruleset into a single matrix. The user consultation session starts by asking questions about the values of premise variables. Once the values of all premise variable in a ruleset retrieved, no matter they were from the data base or from the user interactively, the compositional rule of inference can apply and the value of a consequent variable is deducted. The process repeats until the 'goal' is achieved. Two auxiliaries modules are to handle the interpretation of data, i.e., fuzzy $\Leftrightarrow$ non fuzzy into its appropriate form.

The first task to implement a knowledge system is to select an appropriate computer language. The successful knowledge systems have originally been implemented by a list of languages such as LISP, PROLOG, C, and FORTRAN. Among them LISP and PROLOG are the most widely adopted languages for AI implementation, since they have strong support for symbolic computation. Some other considerations in selecting a language are flexibility of control, support of exploratory programming methodologies, late binding and constraint propagation, and a clear and well-defined semantics. In the case of FRBESS implementation, apart from the above consideration, the support of numerical processing is another factor should be considered, since FRBESS is fuzzy inference system which is different to the production system in the conventional sense. Because of the nature of fuzzy matrix processing the intensive numerical computation is inevitable in all fuzzy inference systems using CRI. Based on these considerations, MACSYMA was selected for FRBESS implementation. Having been Developed by MIT and Symbolics, inc. for over two decades, MACSYMA is a comprehensive 'expert system' for mathematical computing[85,86]. Written in LISP, it is a large, interactive computer algebra system and programming environment designed to assist engineers, scientist and mathematicians in solving a wide spectrum of mathematical problems. The advantages of using MACSYMA for FRBESS implementation are:-(1) powerful symbolic processing ability. MACSYMA is often regarded as a 'symbolic language'. It inherits all LISP's symbolic features such as list processing, and provide a powerful tools for natural language processing. (2) With the build-in 300,000 lines LISP code knowledge base MACSYMA makes the numerical processing much easier and faster. (3) its comprehensive interactive interface provides a nice environment for system development. (4) its build-in LISP compiler and the automated LISP code translation ability provide the familiarity and flexibility to the skilled LISP users. On the other hand, the disadvantages of using MACSYMA are that:-(1) As a high level, expensive language it is not popular in most application environments; (2) with the large knowledge base it requires fairly large amount of computer space for both RAM and ROM. Hence, it makes the language only available on the later large capacity computers. Nevertheless, for the purpose of implementation, MACSYMA seems to be an appropriate tool.

6.3 Knowledge Representation in FRBESS

In general, it is most helpful to understand what kind of knowledge is represented in a system before trying to grasp the representation language. By common usage, knowledge is anything one knows, so it surely includes what is found in the knowledge. But knowledge also includes how things are related. A representation language includes the brevity and the explicitness with which certain kinds of facts can be stated.

The knowledge base contains the facts and rules that embody the expert's knowledge, and there are various ways of representing the knowledge obtained from experts and translated into the knowledge base such as production rules, frames, etc.. The most common inference strategy used in knowledge systems is the application of a logical rule where the rule says, " if A then B", so that when A is known to be true, it is valid to conclude that B is true. Representing the rule in this way , it makes the rule simple and hence the reasoning based on it is easily understood.

6.3.1 Data Representation

Data representation in FRBESS is a set of lists which represent:- (1) facts. The facts list contains the current inference deductions , initial fuzzy assertions, and system data such as component data and configuration list. (2) fuzzy definitions. They are fuzzy linguistic terms definition, hedge operators. (3) auxiliary list. It contains the auxiliary data developed during the inference process. Because of the occurrence of these various different types of data in the problem environment, an unified structure is needed for data representation. Similar to a frame based system, FRBESS employs a general "object-attribute-value" (OAV) triples for data representation. An OAV can be expressed as

The *Attribute* A of *Object* B has *Value* C

Hence, for the problem of reliability prediction and calculation, the data base may consists of data as

(1) Numeric data: ['external_stress, "the_comparative_influence, '5.3]

(2) linguistic data: ['unit_(A), 'failure_frequency, 'monthly]

(3) symbolic data: ['components_list_(X), 'connection, 'parallel]

(4) control data: ['matrix, 'parallel, 'hire]

It should notice that the list representation in MACSYMA syntax is different to that of in LISP syntax. A MACSYMA list has comma to separate elements.

5.3.2 Rule Representation

The structure of rules in FRBESS is a antecedent-consequent pair in which both condition and consequent premises are implemented as the conjunction of OAV triples. For example, a reliability prediction rule defined as

rule1: IF the comparative influence of variance of weather is *positive strong*
AND the comparative influence of variance of maintenance is *negative weak*
THEN the comparative influence of external stress is *more than normal*

The above English like rule is rendered for FRBESS as an OAV structured rule

```
[rule1,
    [con, ['variance_of_weather, 'the_comparative_inference, 'positive_strong],
          ['variance_of_maintenance, 'the_comparative_inference, 'nagetive_weak]],
    ['external_stress, 'the_comparative_inference, 'more_than(normal)]]]
```

In the above rule, 'con' represents the 'conjunction' operation. A rule is formed by three parts: a rule name, a sub-list which contains all condition premises, and a sub-list contains the consequent premise. Each premise sub-list has an OAV structure.

In the fuzzy reasoning technique, the fuzzy production rule format plays a major role in the representation of the imprecision of the problem. The IF-THEN format as stated above is only one possibility that can be found in fuzzy inference system. Other various formats , such as Zadeh's IF-THEN-ELSE format as an example, have their advantageous points depending upon applications. Considerations for selecting a rule format are:-(1) adequately represent the problem solving knowledge; (2) support by a given fuzzy implication operator. Based on these consideration, it has been found that the IF-THEN format is an appropriate choice for FRBESS because that :-(1) the format can be easily arranged into fuzzy CASE format [mamdani 81]. The CASE format is that its IF part rules represent a collection of approximately disjoint and exhaustive conditions, with the THEN part rules all referring to the same output fuzzy variables. This kind of rule structure is useful in systematically eliciting an expert's knowledge about a physical system that is moderately well known such as reliability prediction. On the other hand, rules stated within a CASE statement must necessarily be compact enough so that no knowledge gaps are occurred; (2) The IF-THEN format has the ability to decompose any individual, potentially complicated piece of knowledge into simple implementable rule sets. It can also specify alternative output conditions as in the ELSE part of Zadeh's format. This can be accomplished by introducing to the same antecedent(s) of a new rule a different consequent. In this way, the IF-THEN format can be viewed as a generalisation of the different types of rule format, and is the most suitable format to represent imprecise and uncertain knowledge in FRBESS.

6.4 Design of a Rule Compiler

There are three steps to compile rules in the rule base into an appropriate fuzzy relational matrix form in FRBESS. They are described in the following sections.

6.4.1 Rule Interpreter

The first part of fuzzy inference in FRBESS is to translate the linguistic terms embedded in the rule base into their associated fuzzy sets form. The task is to search rules in the rule base in turn, and to translate the value part of a rule (in linguistic form) into fuzzy set based on the definition of fuzzy linguistic terms which are stored in the data base. If there are linguistic hedges in the rule base. FRBESS will firstly translate the primary terms into fuzzy sets, then apply the hedge operators, which are defined in the data base, on these fuzzy sets. In FRBESS, fuzzy sets are programmed as an array of 11 discrete quantity levels with respect to their universe of discourses and the fuzzy value of a fuzzy variable is represented as a two dimensions 1×11 matrix. As an example, fuzzy set 'high' is defined in FRBESS as

```
Object:=unit_(A)
fuzzy_term:='high
'high[0]:=0.00
'high[1]:=0.00
'high[2]:=0.00
'high[3]:=0.00
'high[4]:=0.00
'high[5]:=0.00
'high[6]:=0.00
'high[7]:=0.22
'high[8]:=0.50
'high[9]:=0.78
'high[10]:=1.00
```

6.4.2 Fuzzy Relational Matrix Generator

To compile a fuzzy production rule into a fuzzy relational matrix, it has two steps as (I) the antecedent parts of a fuzzy rule are first combined together using the fuzzy conjunction rule (equivalent to MIN operation) to form a rule antecedent matrix; (II) through the use of a fuzzy implication operator, the antecedent matrix is then combined with the consequent part of a fuzzy rule to yield a relational rule matrix.

6.4.2.1 Implication Operators Selection

Because the role of an implication operator is vital for the accuracy of a fuzzy inference system, it was examined to select the "adequate" operator for implementing FRBESS.

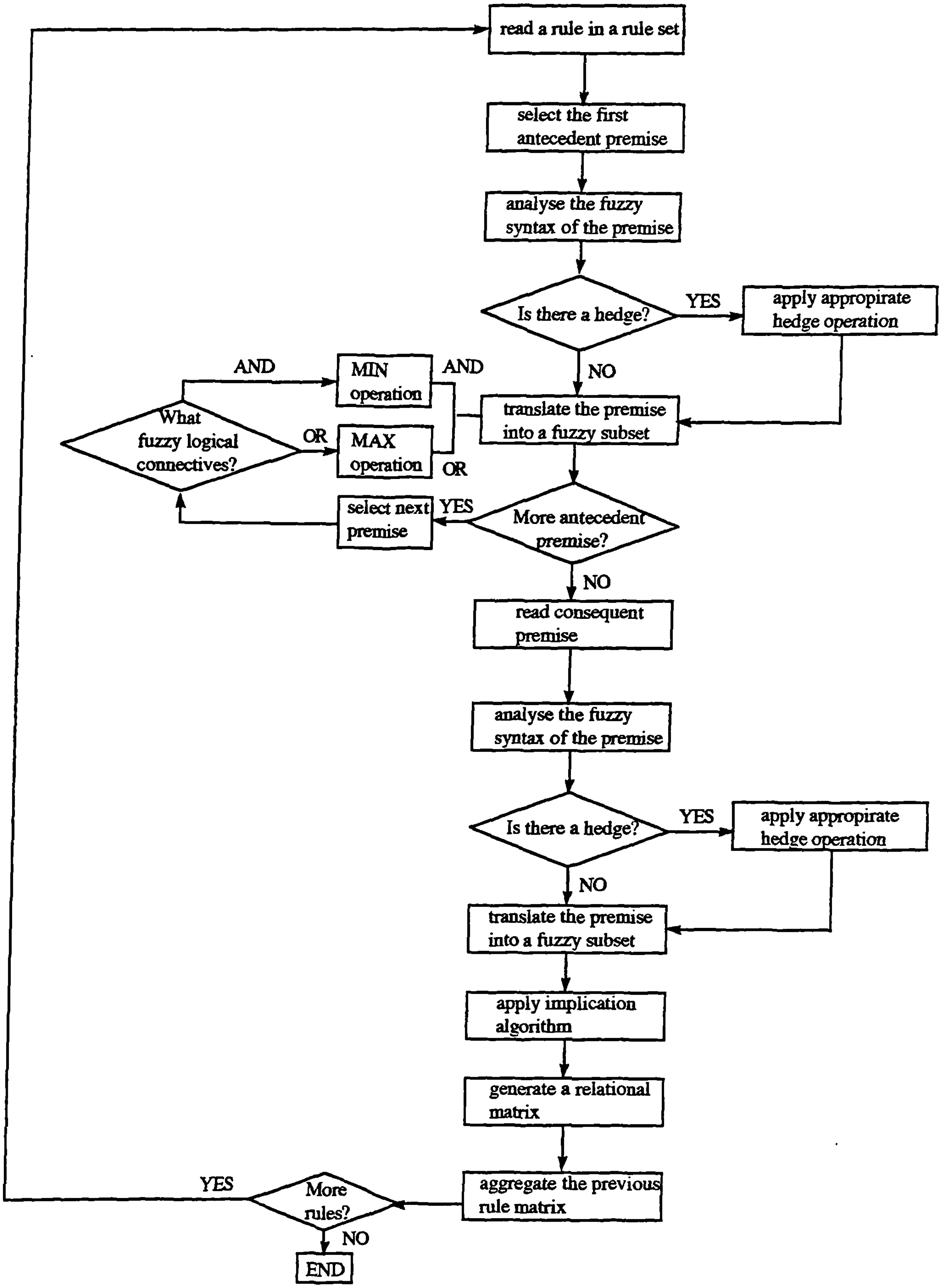


Figure 6.2 Algorithm of Fuzzy Rule Compiler

The study of the generalised modus ponens, initially stated by Zadeh[94] has motivated a lot of research related to the choice of implication operations. A lot of theoretical studies have been conducted into understanding basic characteristics of fuzzy implication operators[22,60,61,62,30]. Mizumoto and Zimmermann[62] have scanned the various existing implication functions so as to classify them according to their behaviour on a set of properties, with emphasis on the transportation of linguistic hedges such as 'very' and 'more or less' from the premises to the conclusion. The studies on the effect of choosing one implication or another on the resulting inference have also been conducted[49,72,77]. In general, it is concluded that there has no unique criteria for judging an implication operator. The preference is largely application oriented.

Implication Operators	Mathematical Equivalent
Lukasiewicz	$A \rightarrow B = \mathrm{MIN}(1, 1 - a_i + b_j)$
Mamdani	$A \rightarrow B = \mathrm{MIN}(a_i, b_j)$
Fuzzy Modus Ponens	$A \rightarrow B = \mathrm{MAX}(1 - a_i, b_j)$
Gaines – Rescher	$A \rightarrow B = \begin{cases} 1 & \text{if } a_i \le b_j \\ 0 & \text{if } a_i > b_j \end{cases}$
Kleene	$A \rightarrow B = \begin{cases} 1 & \text{if } a_i \le b_j \\ \min(1 - a_i, b_j) & \text{if } a_i > b_j \end{cases}$
Godel	$A \rightarrow B = \begin{cases} 1 & \text{if } a_i \le b_j \\ b_j & \text{if } a_i > b_j \end{cases}$

Table 6.1 List of Some Well-known Implication Operators

A popular method of comparing implication operators is that to observe their inference performance by giving various input. Six popular implication operators are listed in table 6.1. An example is given aimed to compare and distinguish among the chosen implication operators to be implemented in FRBESS. Let X be the universe of discourse 'length', X=[1,2,3,4,5], two initial fuzzy sets are defined on X as A=' short' =[1, 0.5, 0.1, 0, 0] and B=[0, 0, 0.1, 0.5, 1]. The composite fuzzy relations between A and B in accordance with the implication operators listed in table 6.1 are given in table 5.2. We consider various types of input as in the following cases:

I. A'=A=[1, 0.5, 0.1, 0. 0]

II.A'=not A=[0, 0.5, 0.9, 1, 1]

III. A'=anything=[1, 1, 1, 1, 1]

IV. A'=unknown=[0, 0, 0, 0, 0]

V. A'=more or less A=[1, 0.7, 0.3, 0, 0]

VI. A'=more than A=[0, 1, 0.7, 0.3, 0]

VII. A'={precise input}=[0, 1, 0, 0, 0]

By using the above fuzzy input propositions A', the corresponding inferred fuzzy output B' for each implication operator are obtained through the MAX-MIN operation. Table 6.2 shows the sensitivities of the inferred result B' under the six implication operators.

The characteristics of each implication operator can be summarised by various cases of using different values of input A' . In case I, the inferred results of fuzzy set B' under Mamdani, Gaines-Rescher, Kleene and Godel implication operators are exactly obtained as B=B', and the result under Lukasiewicz and Fuzzy Modus Ponens are approximately obtained as B≈B'; In case II, none of 6 operators produce a reasonable result. This might be due to the situation where the actions are not able to decide under such conditions. In case III, when the input fuzzy proposition A' is completely uncertain, apart from Mamdani operator all the other operators suggest an output B' with the greatest uncertainty, i.e., B'=A'. As an exception, Mamdani operator produce a certain information B' which is equal to B. In case IV, for all 6 implication operators the inferred results are nil fuzzy set. These results are convinced since it is logically to deduct nothing if nothing is known. In case V, when a linguistic hedge 'more or less' applied there are 3 implication operators, namely Gaines-Rescher, Kleene, and Godel operator, returned the exact solution. In case VI, none of the operators gave the exact solution but the later 3 implication operators delivered acceptable results , when a shift hedge operator was considered in the input . In case VII, Only Gaines-Rescher offered a reasonable approximation.

From the obtained results, it is found that (I) the results obtained by using Lukasiewicz and Fuzzy Modus Ponens implication operators are almost same, so as for

Lukasiewicz

$$R_1 = \begin{bmatrix} 0 & 0 & 0.1 & 0.5 & 1 \\ 0.5 & 0.5 & 0.6 & 1 & 1 \\ 0.9 & 0.9 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Mamdani

$$R_2 = \begin{bmatrix} 0 & 0 & 0.1 & 0.5 & 1 \\ 0 & 0 & 0.1 & 0.5 & 0.5 \\ 0 & 0 & 0.1 & 0.1 & 0.1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fuzzy Modus Ponens

$$R_3 = \begin{bmatrix} 0 & 0 & 0.1 & 0.9 & 1 \\ 0.5 & 0.5 & 0.5 & 0.5 & 1 \\ 0.9 & 0.9 & 0.9 & 0.9 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Gaines - Rescher

$$R_4 = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Kleene

$$R_5 = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0.1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Godel

$$R_6 = \begin{bmatrix} 0 & 0 & 0.1 & 0.5 & 1 \\ 0 & 0 & 0.1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Table 6.2 Fuzzy Relational Matices Generated using Different Types Implication Operator

Case	R_1	R_2	R_3	R_4	R_5	R_6
I	[0.5, 0.5, 0.5, 0.5, 1]	[0, 0, 0.1, 0.5, 1]	[0.5, 0.5, 0.5, 0.5, 1]	[0, 0, 0.1, 0.5, 1]	[0, 0, 0.1, 0.5, 1]	[0, 0, 0.1, 0.5, 1]
II	[1, 1, 1, 1, 1]	[0, 0, 0.1, 0.5, 0.5]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]
III	[1, 1, 1, 1, 1]	[0, 0, 0.1, 0.5, 1]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]	[1, 1, 1, 1, 1]
IV	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]
V	[0.5, 0.5, 0.6, 0.7, 1]	[0, 0, 0.1, 0.5, 1]	[0.5, 0.5, 0.5, 0.9, 1]	[0, 0, 0.3, 0.7, 1]	[0, 0, 0.3, 0.7, 1]	[0, 0, 0.3, 0.7, 1]
VI	[0.7, 0.7, 0.7, 1, 1]	[0, 0, 0.1, 0.5, 0.5]	[0.7, 0.7, 0.7, 0.7, 1]	[0.3, 0.3, 0.7, 1, 1]	[0.3, 0.3, 0.7, 1, 1]	[0.3, 0.3, 0.7, 1, 1]
VII	[0.5, 0.5, 0.6, 1, 1]	[0, 0, 0.1, 0.5, 0.5]	[0.5, 0.5, 0.5, 0.5, 1]	[0, 0, 0, 1, 1]	[0, 0, 0.1, 1, 1]	[0, 0, 0.1, 1, 1]

Table 6.3 Comparison of the Results Obtained Using Different Types Impication Operator

the results obtained by using Gaines-Rescher, Kleene, and Godel implication operators, so that these 6 implication operators can be divided into 3 groups with Lukasiewicz etc. as the first group and Mamdani implication operator as the third group. Sembi(1980), and later Chui (1989)[ ] had discussed two important factors for assessing implication operators' relative merits as the 'characteristics' and 'inclusiveness'. From the above results it can be observed that the first group operators (Lukasiewicz etc.) are the most inclusive implication operators. Hence, the inference using these operators are relative vague and likely the less realistic solution will be deducted. On the other hand, Mamdani implication operator is the most less inclusive implication operator among the listed 6 operators, and the inclusiveness for the group of Gaines-Rescher etc operators is somehow in between the another two groups; (II) The less inclusive implication operator such as Mamdani implication operator requires strong evidence to support B if A is established. Therefore it is applicable when an exhaustive set of conditions is known. It further requires that no major knowledge gaps such as in CASE knowledge structure. On contrast the Lukasiewicz group operators are more flexible than Mamdani and Gaines-Rescher group operators.

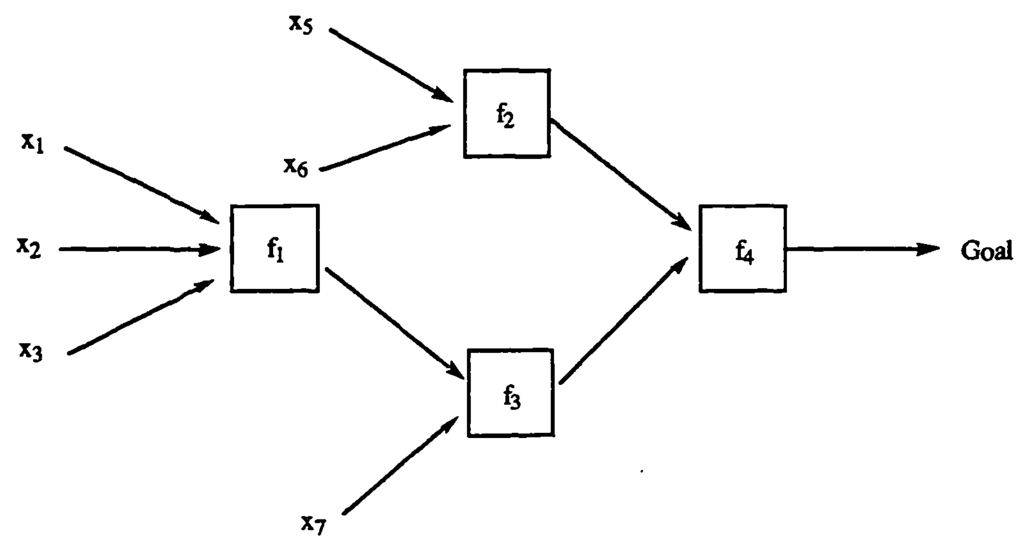


Figure 6.3 A Conceptual Rule Model

As a conclusion it is found that both Gaines-Rescher group implication operators and Mamdani implication operator are applicable to the problem of reliability prediction and calculation, where the inherent uncertainty of knowledge is to a moderate extent and the knowledge gaps can be reduced to a acceptable level by carefully organising the IF-THEN rules. The Gaines-Rescher group implication operators are more preferable since they have the better performance when the hedge operations (both shift and power) emerged, which is the situation frequently occurred in constructing a knowledge base. Above all, the Gaines-Rescher is the 'best' implication operator within the scope of comparison performed in the above cases studies.

However, bearing in mind that FRBESS is tend to be designed as a generalised fuzzy expert system shell, it is necessary to consider all possible situations where a user may prefer to have alternatives in selecting an appropriate implication operator for his problem solving domain. Based on such consideration, FRBESS is designed to offer the options for users to select any one of 4 programmed-in implication operators. These programmed implication operators are Lukasiewicz, Mamdani, Gaines-Rescher and Godel operators. During a consultation session FRBESS will prompt first for a user to select his preferable implication operator before it starts to compile rules.

6.4.3 Rule Matrix Aggregation Algorithm

The last task for rule matrix generator is to aggregate all generated single rule matrices into a ruleset matrix. A set of fuzzy rules represented in a CASE (see last section) structure is connected by 'ELSE', such as in the format of " If X is A_1 Then Y is B_1" ELSE "If X is A_2 Then Y is B_2" ELSE ......ELSE "If X is A_n Then Y is B_n".

The most popular definition for ELSE connective operation is to treat it as the same of disjunction operation. A disjunction operation compares two grade of memberships and selects the smaller one. It can be represented as MIN operation. Hence, the aggregation of rules in a ruleset is achieved by a disjunction operation (or MIN) on

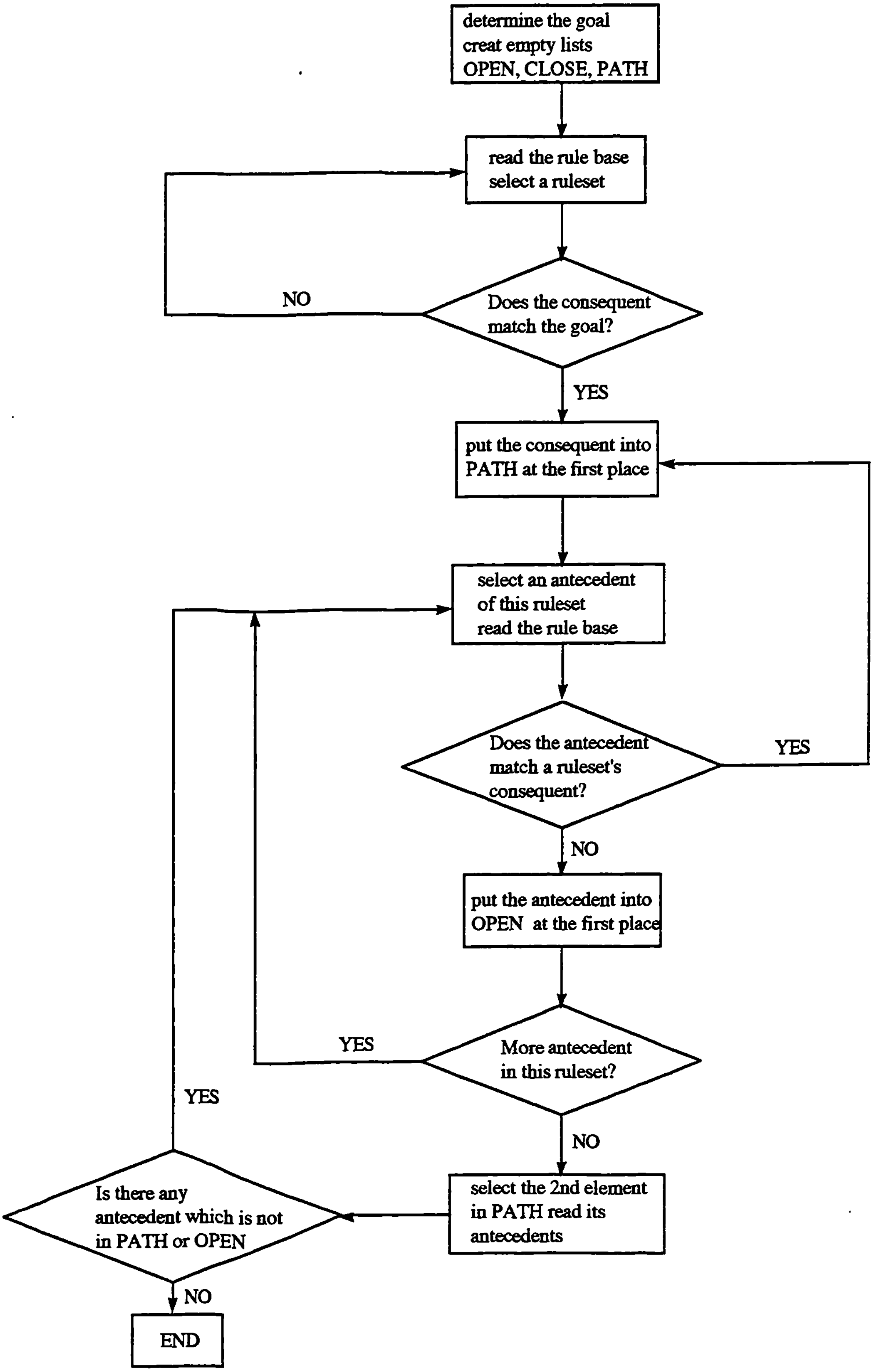


Figure 6.4 A Decision Variables "Chaining" Algorithm

all rule matrices. If there are N rules in a ruleset, each individual fuzzy relation in every rule is aggregated to form an overall R of the ruleset as

$$R = \bigcup_{i=1}^{N} R_i \qquad \text{eqn 6.1}$$

where $\bigcup$ denotes MAX operator (fuzzy disjunction). The complete rule compiling Algorithm in FRBESS is graphically shown in figure 6.2.

6.5 Design of a Fuzzy Inference Mechanism

The fuzzy inference mechanism in FRBESS consists of two major program blocks: an inference sequence control module; and a fuzzy compositional of rule inference module. They are described in the next sections.

6.5.1 Decision Variables Chaining Algorithm

To permit fuzzy inference to be carried out in a logical manner which reflects not only the problem structure but also the intrinsic relationship (i.e.) chaining among decision variables, three lists which represent the tree structure of a problem solving strategy are necessary to be constructed. An inference sequence control can be implemented using these lists.

In FRBESS, it provides a build-in backward depth-first chaining facility using the 'chaining' commend. Also it allows user to define their own chaining strategy in terms of inputting three lists into the rule base in the meta rule form.

A conceptual rule model can be represented as shown in figure 6.3, where X is 'leaves' of the tree representing 'root' decision variables. N is a set of 'node' of leaves intermediate decision variables or sub-goals. Once the inference goal is determined, A "chaining" algorithm is used to extract the relationships among decision variables from the inference rules. These relationships are represented by three lists named OPEN, CLOSE and PATH.

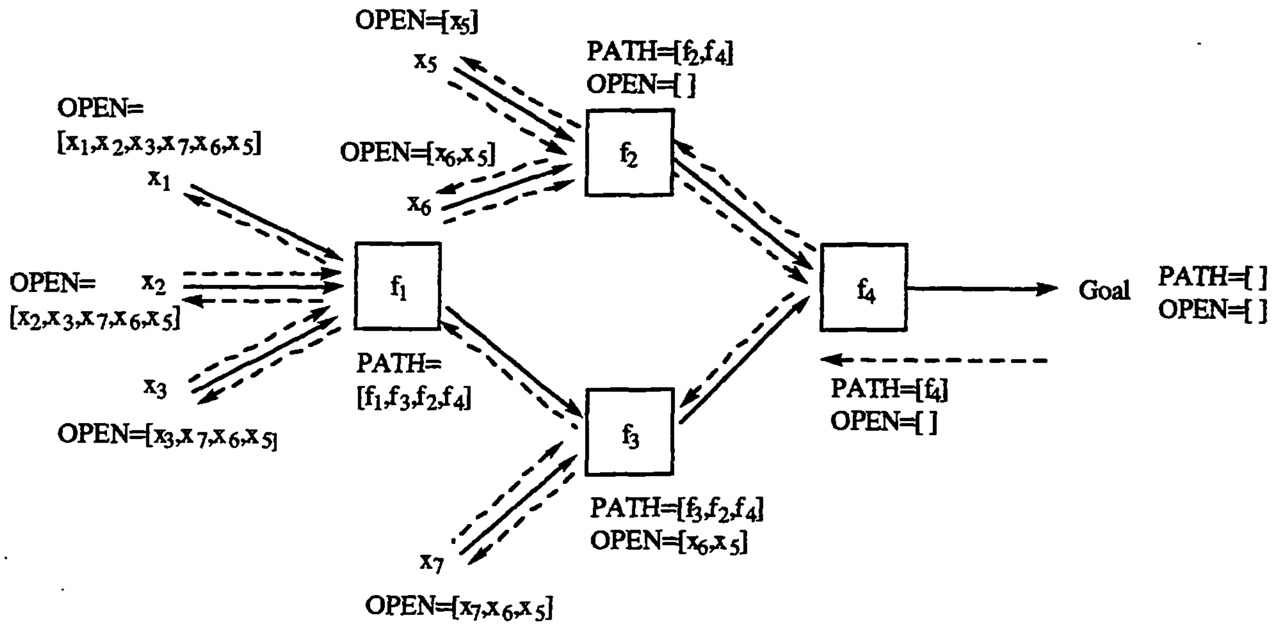


Figure 6.5 Illustration of the Backward Depth-first Searching Strategy

---

A PATH list contains the name of all intermediate decision variables (sub-goals) and decision goal , which are extracted from the inference rules in the rule base. The name of the decision variables in PATH list is in accordance with the name of the aggregated ruleset matrix, so that when an element of PATH list is called then its corresponding fuzzy relational matrix is instantly hired for reasoning. A OPEN list contains the name of all 'root' variables. The variables in OPEN list are waiting to be called when an element of PATH list is selected. When a variable of OPEN list is called, the data of this variable is put into the working memory as the input of a condition premise ready for reasoning. To speed inference process, the elements in OPEN and PATH list are arranged in orders (in accordance with the forward reasoning sequence) so that it does not need to search the whole list to find a expected element. A CLOSE list is initially an empty list. Once the data of a variable of OPEN list is retrieved, the name of this variable is then moved to CLOSE list, so that when a reasoning session finished the CLOSE list should contains the name of all variables initially in the OPEN list.

An algorithm for chaining decision variables in a rule base and construct three lists using backward depth-first searching technique are shown in figure 6.4. The

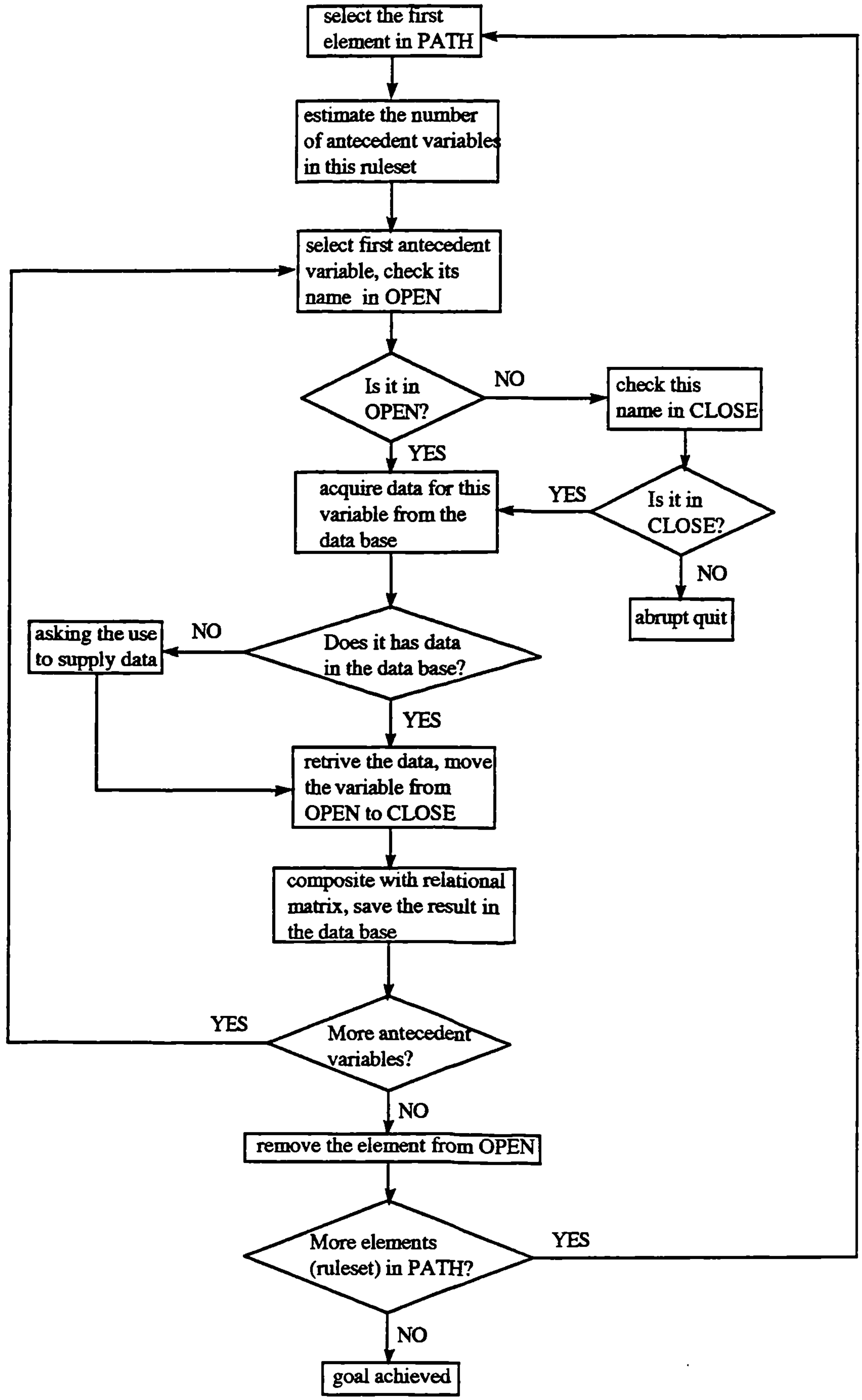


Figure 6.6 Algorithm To Control Forward Reasoning Sequence

backward depth-first chaining technique is better to be demonstrated graphically in figure 6.5, which uses the same conceptual model shown in figure 6.3.

6.5.2 Inference Sequence Control Algorithm

The control of inference sequence for a problem solving which can be represented by a tree structure is quite simple. A tree represented knowledge model implies that each ruleset in this model is hired only once during a consultation session, such as the case for a conceptual rule model shown in figure 6.3. A PATH list generated as stated in section 6.5.1 has embedded forward reasoning strategy. A forward reasoning is that based on the condition of all root variables are known it is to infer from the bottom of a tree to the top (goal). The PATH list and OPEN list have their elements arranged in order with the forward reasoning sequence: start form the first element (ruleset) of PATH list, FRBESS selects those condition evidence (elements) in OPEN list and retrieves their data either from the data base (if any) or from the use by asking queries. By applying CRI algorithm the first element of PATH is inferred, this sub-goal is then stored into the data base and the name of ruleset is removed from PATH list. The process will repeat from the first element in PATH list again until the PATH list becomes an empty list. At the stage when PATH and OPEN lists are empty and CLOSE list contains all root variables, the reasoning goal is achieved. The algorithm for control of a forward reasoning sequence is shown in figure 6.6.

However, in some applications the control of reasoning sequence is a relatively complicate task. For example, the inference sequence for a rule-based reliability calculation is in an iterative manner, i.e., a ruleset is hired repeatedly to deduct a desired goal. Based on such consideration, FRBESS has been designed to offer the maximum flexibility in the reasoning sequence control, in terms of allowing an users to define his own control strategy by inputting a set of meta rules into the rule base. The meta rule set named SDIS (Self Defined Inference Sequence) must be written in MACSYMA syntax and is compiled by FRBESS into LISP execution code after the rule base was loaded. By

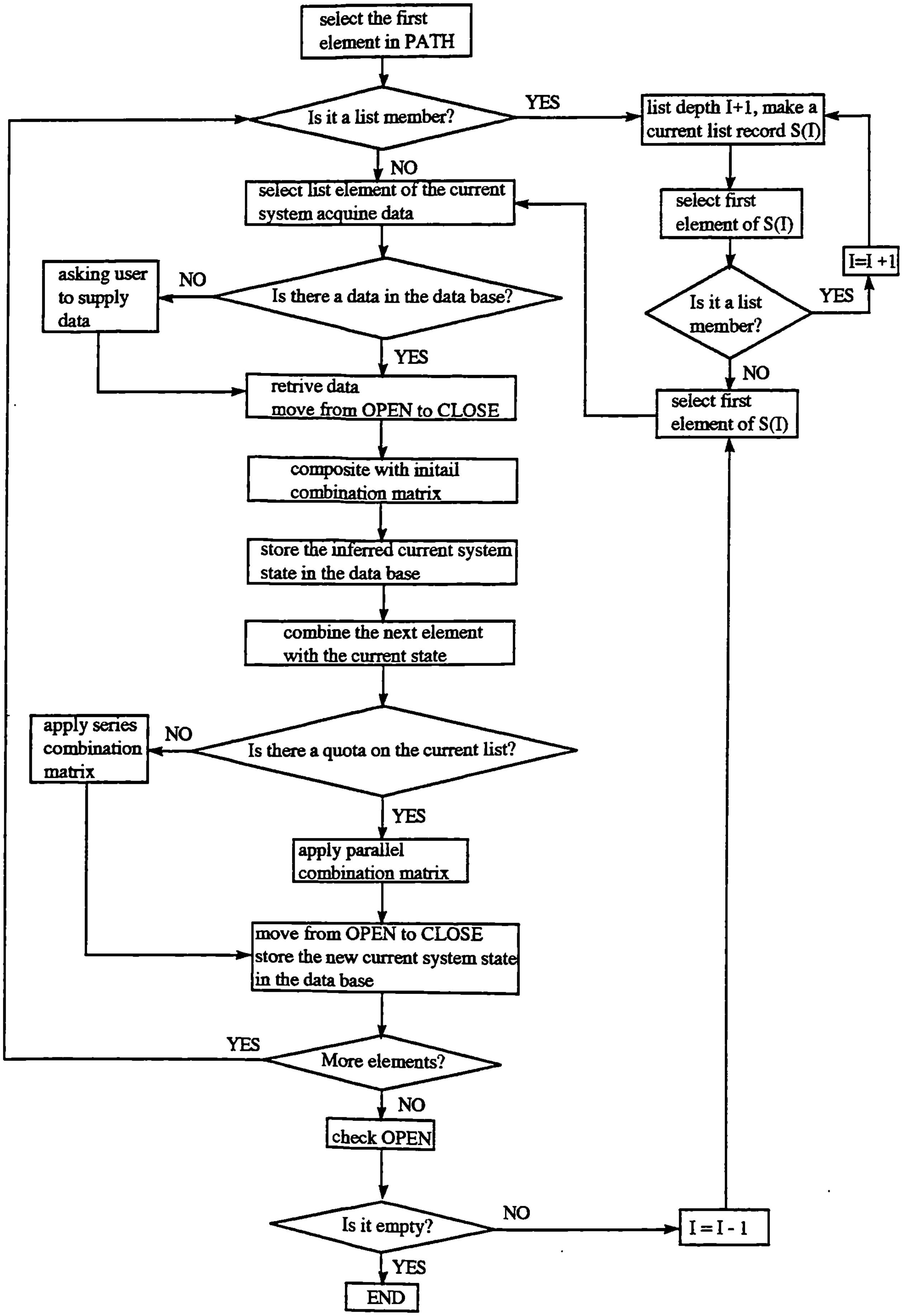


Figure 6.7 Algorithm To Control Reliability Combination Reasoning Sequence

using a command "switch" FRBESS will replace the build-in forward reasoning control module by SDIS, which is then linked in FRBESS.

SDIS must be implemented by using three lists. In the case of the fuzzy rule-based reliability calculation, these three lists are generated by a "sorting" algorithm. Briefly, sorting process is to rearrange the system configuration list given in the data base, into the form that the most nested sub-list should be put at the first place. Once the reasoning priority is determined, these elements will then be put into a PATH list for reasoning.

The algorithm for control of inference sequence in the fuzzy rule based reliability calculation model is shown in figure 6.7. The aggregated fuzzy ruleset matrix for parallel and series connected units combination are hired in sequence under the control.

6.5.3 Compositional Rule of Inference (CRI) Algorithm

The last part of the inference algorithm is to produce or infer possible solutions from external assertions to the relational matrix. The general structure of this algorithm is based on the compositional rule of inference defined in eqn 3.11,

$$B' = A' \circ R_{A \to B} \qquad \text{egn 6.2}$$

where A' is a fuzzy assertion and B' is an inferred consequent corresponding to A'. The operation on their membership functions is as follows:

$$\mu_{B'}(y) = \vee(\mu_{A'}(x) \wedge \mu_R(A,B)) \qquad \text{eqn 6.3}$$

where $\wedge$ and $\vee$ are maximum and minimum fuzzy operations respectively between the matrix A and matrix B. Its effect is to use A" to reduce the dimensionality of matrix "R" to that of the same order of matrix B. If there have a couple of fuzzy assertions, it is to composite these assertions one by one to the relational matrix. The final inferred fuzzy conclusion is always in a vector form (fuzzy subset, or possibility distribution).

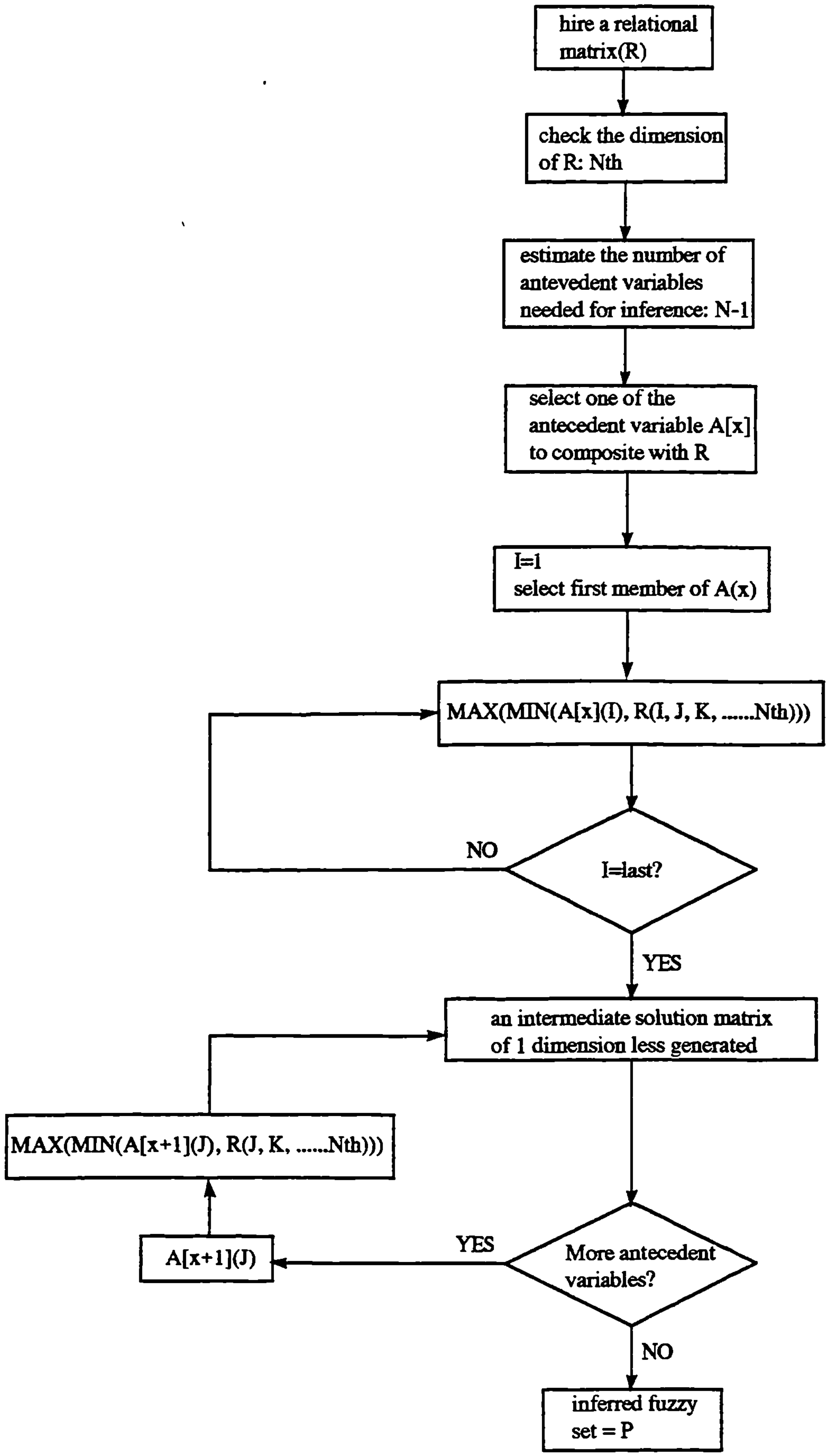


Figure 6.8 Compositional Rule of Inference Algorithm

A fuzzy compositional rule of inference algorithm in FRBESS is shown in figure 6.8. Because of the mathematical structure of CRI, it inevitably involves multi-dimensional matrices computation. To improve the computing efficiency for FRBESS, it adopts two methods as (1) restrict the number of antecedents in a rule is no more than 5. The rule has more than 5 antecedents can be rectified by artificially assigning an intermediate sub-conclusion, then divided by two linked rules. (2) prior to a consultation session, the relational matrix are off-line generated and stored in the computer. The experience shown that the large amount of computing time are consumed by high dimensional matrices calculation. The computing time for actual inference is relatively tolerable.

6.6 Design of a Information Processor

For a fuzzy inference system, the input for the various applications may be in the format of a numeric (both singleton and interval)or a linguistic expression. The output under the request may need a graphic plot display in addition to the numerical and linguistic output. Therefore, there has to implement an input and output control module for FRBESS.

In the information processor module, prior to any data processing the first task is to determine an unique level for the universe of discourse of all variables to be inferred. In FRBESS, a 11 elements array is defined as the arbitrary universe. All the real universe of variables are mapped to this universe of discourse using eqn 3.3. When the possible solution is inferred, the result can be transferred back to the original universe by using the reciprocal function of eqn 3.3.

6.6.1 Translation of Non-fuzzy Data

The process of translating a numerical input into fuzzy subset is called "fuzzification". Two types of likely numerical input are considered: numerical singleton

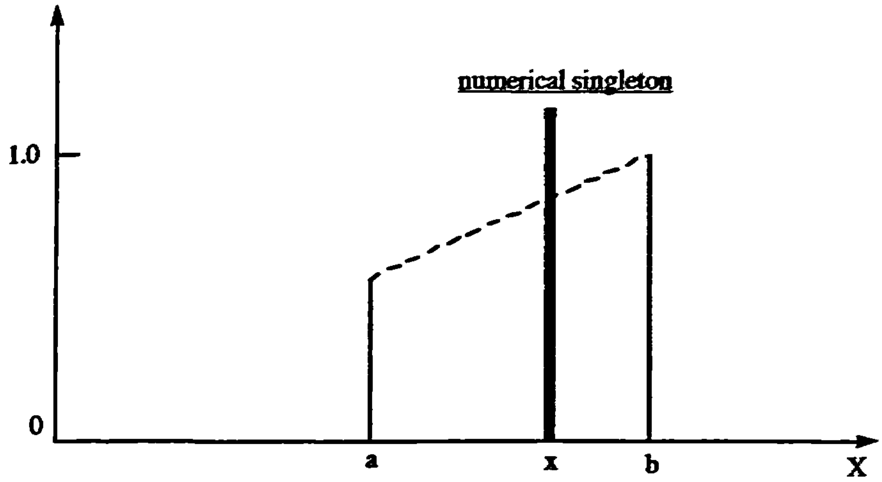


Figure 6.9 Translating Numerical Data Into Fuzzy Data

and interval. In FRBESS, the numeric singleton can be fuzzified via using the following function as

$$\mu(a) = \frac{x-a}{b-a}; \qquad \mu(b) = \frac{b-x}{b-a} \qquad \text{eqn 6.4}$$

where a and b are two point values on a universe of discourse, x is a numerical singleton between a and b, $\mu(a)$ and $\mu(b)$ are the grade of membership of x at a and b respectively. The above definition agrees with intuitive meaning that if x is more close to b then the possibility of x at b is higher than the possibility of x at a. Similarly, a numerical interval can be translated into a fuzzy subset by

$$\mu(a) = \frac{b-x_1}{b-a}; \qquad \mu(b) = \frac{x_2-a}{b-a} \qquad \text{eqn 6.5}$$

where a and b are two point values on a universe of discourse, x_1 and x_2 are the left and right point of a numerical interval, x_1 and x_2 are within the interval [a, b]. If a numerical interval crosses one or more points of a universe of discourse, then a, b are the points which a left or right interval point is in between. The grade of memberships for the crossed points of universe of discourse are 1.0. The fuzzification of a numerical input is show in figure 6.9.

6.6.2 Compression of Fuzzy Data

Under the situation that an inferred possible solution should be output as a crisp value, such as in the case of industrial control, FRBESS has the programmed fuzzy data compression facility which is based on the Centre of Gravity (COG) method. The compressed fuzzy value using COG is calculated by weighting all the elements in the universe of discourse of X with their membership values. The COG method can be expressed as

$$C = \frac{\sum_{i}^{n} x_i \times \mu(x_i)}{\sum_{i}^{n} \mu(x_i)} \qquad \text{eqn 6.6}$$

where x_i is the point value of a universe of discourse, $\mu(x_i)$ is its associated membership value. The merit of the COG method is that it counts in all the possible values on a universe of discourse. The strenth of using COG is particular demonstrated when all ill-structured fuzzy values are presented, such as it is shown in figure 6.10.

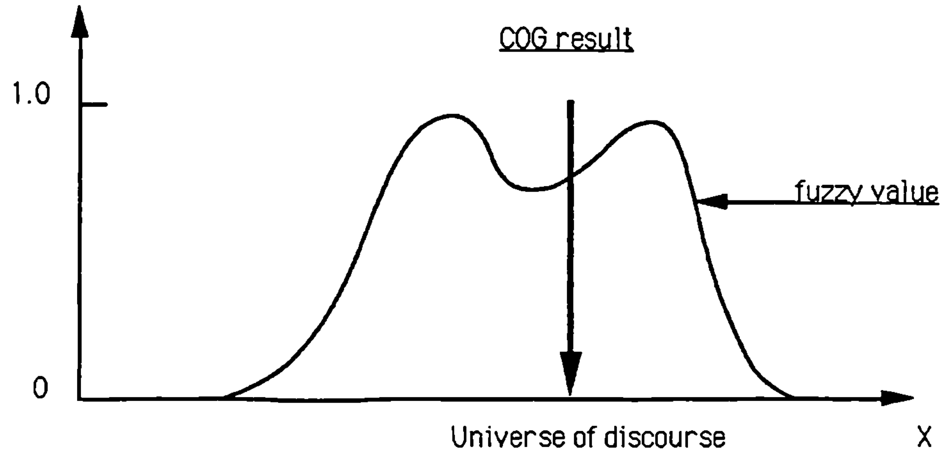


Figure 6.10 Compression of a Fuzzy Value

6.6. 3 Linguistic Approximation

The last type of man-machine communication during a consultation session is linguistic expression of an inferred solution, which is computed in FRBESS by a process called 'Linguistic Approximation' (LA). LA is a re-translation procedure of the possibility distribution into its equivalent linguistic proposition, such as "less than normal but not weak".

The method used in FRBESS to translate a possibility distribution into its linguistic expression is the least distance method. The least distance method is expressed mathematically as

$$N(A,B) = 1 - \frac{1}{n}\sum_{i}^{n} (A(x_i) - B(x_i)) \qquad \text{eqn 6.7}$$

where A is inferred fuzzy set and B is a pre-defined linguistic term. If N is 1.0 then A is translated as B, In general the smaller N is the less similar two fuzzy sets are. In FRBESS, algorithm for linguistic approximated was programmed as: (1) calculate the distances between inferred fuzzy set A and all primary linguistic terms. If there has a N_i which is 1.0 then translate A into ith linguistic term, otherwise (2) select two linguistic terms T_1 and T_2 which have the biggest values of calculated N, apply hedge operation on T_1 and T_2, re-calculate N for T_1 and T_2.(3) select the minimum N. Translate the inferred fuzzy set into the corresponding linguistic term.

To obtain a meaningful linguistic approximation, some consideration were also programmed into FRBESS. These are:-(1) for the sake of computing efficiency, only a limited number of hedge operators are selected for measuring distance. The selected shift operators are: more than, less than, and between. The selected power operators are: very, more or less, not. (2) the sequence of applying hedge operation is that the shift operators firstly are called first. (3) If there have two Ns and the corresponding linguistic terms are next to each other, apply hedge 'between' first. (4) a threshold is given in FRBESS as 0.8. The hedge operation should be continuously applied until a N which is equal or great than 0.8 is obtained. Hence, in the case of reliability calculation the process of linguistic approximation returns an output such as ' The failure frequency of 50 MW hydro unit is between(less_than(yearly), more_than(more_than(monthly)))'.

6.7. Command Environment of FRBESS

By typing 'help' command, FRBESS will list a set of commands on the screen. These commands are:

```
load < filename >        -load data-base, rule-base etc.
display <arg >           -display rules, data etc.
determine <var >         -determine reasoning goal
compile <arg>            -compile rules into the matrices form
chaining <arg>           -construct reasoning path using backward depth-first searching method
infer < var>             -Infer goal using CRI method
help < arg>              -list all commands or files under the current directory
save <filename>          -save the consultation session into a named file
print <filename>         -print out a named file
compress <var>           -perform fuzzy data compression
express <var>            -perform linguistic approximation
plot <var>               -plot the possibility distribution of an inferred fuzzy variable
edit <arg>               -edit data-base and rule-base.
switch<arg>              -link an user defined process to the system
why < >                  -explain why a query is needed to be answered
reset < >                -remove all data in the working memory
bye < >                  -end of consultation
```

The communications between a user and the system are in an interactive manner. FRBESS was implemented on a SUN SPARC station using MACSYMA. The environment of user interface provided by both hardware and software is friendly enough so that no further efforts wasted on developing a 'user friendly interface'.

One important feature for a real knowledge based system is that it should consist of an explanation facility. Such feature was implemented in FRBESS. An explanation for why a particular query to be answered by a user in a FRBESS session is:

```
***what is the_comparative_influence of variance_of_maintenance?
why;

***The reason for asking question is that the ruleset "external_stress" is currently being hired.
*** It has already been established that
*** Hypothesis: variance_of_weather
*** It is aid in concluding the sub-goal "external_stress" by determining
*** Hypothesis: variance_of_maintenance
***what is the_comparative_influence of variance_maintenance?
nagetive_weak;
```

6.8 The Concluding Remarks

In this chapter, the design and key aspects of a fuzzy rule-based expert system shell(FRBESS) have been discussed. This principally consists of selecting the appropriate data and rules representation format, and devising efficient algorithms for rules compilation, compositional rule of inference, and input/output data process. The discussed system has been implemented in the form of a software package named FRBESS by using MACSYMA computer language. FRBESS has been tested by using proposed reliability prediction and calculation (see case studies, chapter 3 and chapter 4).. It has also been tested by using Terjersen's energy forecasting model and Chui's voltage/var control model. The result has shown that FRBESS is a generalised fuzzy knowledge based system.

Chapter Seven

Conclusions

7.1 Summary

The introductory part of the thesis examines the general uncertainty problems which affects the decision making process in reliability analysis, and the relevant problems in power system reliability evaluation within the scope. The importance of utilising human knowledge and taking human judgmental advice has contributed to yield better decision in some obscure situations where mathematical description can not be achieved. With the aid of nowadays computer technology, it has discovered that the knowledge based system with human experts' knowledge representational and inferential capability are capable to aid reliability analyst to make quality evaluation. The inherent uncertainties associated with the knowledge based system have been addressed. The various current approaches attempting to manage the uncertainty have been stated and discussed. Through the investigation, the important role played by human experts in reliability evaluation has been established. Human experts judgmental knowledge are expressed naturally in linguistic rather than numeric. Therefore, the uncertainty concerned in knowledge representation and inference process is mainly fuzziness. Motivated by this observation, a new reliability analysis formulation is proposed based on the newly emerged innovative concepts such as Fuzzy Set Theory and Fuzzy Reasoning.

The basic concepts and techniques of the conventional probability reliability evaluation were presented in chapter 2. The general ingredients of an overall reliability prediction have been underlined as (1) device reliability prediction; (2) device maintainability prediction and human operators error prediction. The definition and usage of various reliability indices were illustrated. The importance of adequate estimation of basic reliability indices were also addressed, since the accuracy of a system reliability assessment depends upon the adequate estimation of device reliability indices. The speciality consideration for reliability indices estimation was emphasised, for the current probability approach pursues the 'generality' of a system reliability performance. However, because of the limitation of the techniques in use, e.g., sample size, variance of test methods, environmental conditions etc., the estimated reliability indices using the conventional statistical method usually do not permit the generality. Therefore, the speciality study must be conducted in any reliability prediction process.

With the awareness of the importance of speciality consideration in reliability prediction, the deficiency of using probability techniques to evaluate the situational factors was addressed. It was found that because of the variability and complexity of determining the situational factors, it is incapable to evaluate the situational affects on reliability performance in terms of statistical method. Therefore, the situational factors in reliability prediction are largely determined subjectively based on reliability experts' experiences and knowledge. The uncertainty associated in such subjective knowledge is fuzziness in nature rather than randomness, as it has been well argued by Zadel and man others. Based on this, a fuzzy rule-based model for predicting device reliability was presented in chapter 3. The source of uncertainty in reliability prediction was carefully studied. It has been discovered that the uncertainty may exist under two situations:- (1) it is completely lack of statistical information or the available records are not sufficient. In this case the human experts' subjective estimation is the sole 'reliability' source, and the human being's thought and expression are imprecise in nature. (2) It is impossible to determine the relationship between a device reliability performance and a situational factors. The experienced reliability engineers can remedy this problem to some extent, however, his/their judgement inevitably consists of the inherent uncertainty. Hence, Some commonly emerged situational factors were identified and their relationships with a device reliability performance were established in the form of a class structure. Three sub-models were proposed, namely device failure possibility prediction, device total maintenance time prediction and human operators error possibility prediction. The model was built based on Zadel's powerful Fuzzy Set Theory and Fuzzy Reasoning. Reliability

Experts' prediction knowledge was represented in a set of fuzzy rules and organised into the well-known "IF-THEN" production rule format. By inputting his estimation of a device failure, maintenance time and human error possibility into the presented fuzzy reliability prediction model, a reliability analyst should have an overall assessment on the reliability performance of this device. This objective was achieved as demonstrated by the results obtained from the case studies

The methodology of combining individual device reliability to assess reliability performance at system level under the fuzzy environment was presented in chapter 4. Two important fuzzy techniques were employed for this purpose, namely fuzzy arithmetic and the possibility theory based fuzzy reasoning. In fuzzy arithmetic approach the individual reliability indices were modelled as the parametric fuzzy numbers or converted to well-format fuzzy numbers if the inferred indices from fuzzy prediction model were ill-structured. A set of reliability combination operations were defined based on the extension principle, and carried out by manipulating a few parameters of the fuzzy numbers. In fuzzy rule-based approach, fuzzy individual device reliability indices are modelled as a set of linguistic terms on a finite discrete set. The reliability combination were carried out using Compositional Rule of Inference method, together with a carefully designed inference control algorithm. Both approaches delivered the convinced results in case studies. The former approach has the merit on computing efficiency, however its data format is rigorous. The later approach compromises on data format since it is able to accommodate and process any type of fuzzy value defined on a universe of discourse. Hence, it has the consistence with the device reliability prediction model, and two model can be integrated together so that an overall system reliability performance can be inferred.

The proposed fuzzy reliability techniques were extended to the area of power generating system adequacy evaluation , where the aim of reliability analysis is to measure the adequacy of the supply of a generation system to satisfy a load demand. The source of fuzziness in generating system reliability evaluation was stated and discussed in chapter 5. Because of the fuzziness existed in both unit reliability data and forecast load data, these data were modelled as triangular fuzzy numbers. The presented methodology for convoluting both fuzzy generating model and fuzzy load model was based on the concept of fuzzy containment, i.e., the degree of a fuzzy load level contained in a fuzzy capacity in service state. An new possibilistic index named Possibility Of Load Loss(POLL) was defined and the algorithm to calculate this index was given. The proposed fuzzy generating system reliability evaluation model was tested on RTS. The results obtained proved the validation of the model.

A fuzzy rule-based expert system shell (FRBESS) for reliability evaluation was implemented. The structure of FRBESS and its key features were presented in chapter 6. FRBESS is a fuzzy inference system which consists of a knowledge base(rule and data), a rule compiler and an inference mechanism. The implemented inference method is fuzzy compositional rule of inference. FRBESS has been applied to the cases studies in chapter 3 and chapter 4.

7.2 Original Contributions

Application of knowledge based system to reliability evaluation alone is a relatively new research. With the participation of fuzzy arithmetic and fuzzy reasoning, the major contributions of this thesis are summarised in the following:

(a) The fundamental uncertainty problem structures in general reliability prediction were analysed. Through the study it discovered that there are two major concepts in reliability predictions: the basic estimations which reflect the design, manufacture characteristics of a device, and the adjustment factors which reflect the usage and environment characteristics. The inherent imprecision and uncertainty in reliability prediction were then explored. An overall reliability prediction was defined as the integration of three sub-predictions: device failure prediction, device maintenance time prediction and human error prediction. Human experts' role in these reliability predictions were emphasised under the situations such as (I) when the basic estimations are unavailable or insufficient; and (II) to determine the relationship between the situational factors and a device reliability performance, and estimate the degree of such effects.

(b) The affection of situational factors on reliability performance was analysed. The concept of 'speciality' was emphasised on contrast to the concept of generality in probability reliability prediction. Various types of commonly emerged situational factors in reliability prediction have been studied, and the relationship between a device reliability performance and its affecting situational factors was established. These relationships were represented in the form of a set of decision trees, so that the knowledge of reliability prediction can be easily acquired from these trees and represented in a IF-THEN production rule form.

(c) A fuzzy knowledge based reliability prediction model was developed. The model is free to accommodate and process any type of information (linguistic and numeric). Reliability prediction techniques and strategies were modelled as a set of fuzzy production rules. The process of reliability prediction is therefore automated. The model is in the stream of Knowledge Based Systems (KBS) with the participation of fuzzy concepts.

(d) A computationally vary efficient fuzzy arithmetic reliability calculation method was developed. The conventional probabilistic reliability combination rules were extended to include the capability of combining individual device with fuzzy reliability data . Various fuzzy reliability indices were defined based on this extension.

(e) A fuzzy knowledge based system reliability combination model was developed. The knowledge of reliability combination was induced into the form of fuzzy production rules. An effective combination reasoning sequence control algorithm was also developed.

(f) The proposed fuzzy reliability techniques were extended to the area of power generation system reliability evaluation. Both fuzzy generating capacity model and fuzzy load model were developed. By convoluting these two models using a developed fuzzy containment algorithm, a new index for generating system reliability evaluation was defined as Possibility Of Load Loss (POLL).

(g) The proposed index POLL was applied to Reliability Test System(RTS) to highlight its applicability and test its validation. The results obtained were analysed in comparison with the results obtained using conventional probabilistic techniques.

(h) A Fuzzy Rule-based Expert System Shell was implemented on MACSYMA. Using FRBESS, the proposed fuzzy knowledge based reliability prediction and calculation model were tested through two case studies. The programmed FRBESS also provides a basis for further research.

7.3 Research Extensions

The problem of applying AI techniques to reliability analysis has only been touched in this dissertation. The scope of research extension in these areas is immense, Areas which to the author's belief are grounds for fruitful further research are identified in the following:

(a) With respect to reliability evaluation, two directions of further development can be pursued:- (1) developing a fully integrated fuzzy linguistic inference model which can be used in reliability prediction and calculation under the fuzzy environment. Such model shall have full flexibility to handle all possible situations with an inference engine which can effectively handle fuzzy and non-fuzzy data. (2) Further exploring the inherent uncertainty in reliability analysis. The relationship between situational factors and reliability performance is still vague. Besides, various failure modes should be carefully studied, e.g., common mode failure.

(b) With respect to the application of fuzzy reliability techniques to power system, further research may conduct in developing a fuzzy knowledge based method to generating capacity model. It has been recognised for long that the recursive techniques for constructing a system capacity outage table is too time consuming. For a large system with many different types generating units it is extremely difficulty to produce such table so that it can be convoluted with the load model to determine a system risk level. Many attempts for remedying this problem in terms of calculating a capacity outage state probability directly have been reported. Human experts' heuristic knowledge may help to solve this problem to a certain extent. A fuzzy rule may be stated as " IF there are two types of unit combined in the system AND the first type consists of *a few* numbers of units with *fairly large* unit capacity as well as *more or less high* forced outage rate AND the second type consists of *many* numbers of units with *small but not too small* capacity as well as *very low* forced outage rate, THEN the chance of a *medium* size capacity outage is very *probably*". The representation and inference mechanism for this type of knowledge need to be carefully studied. This type of knowledge can be extended to evaluate system risk by entering a peak load condition premise. Furthermore, the fruitful future research may be conducted in extending fuzzy knowledge based approach into power generation expansion planning where the economical constraint and future load demand can be treated as fuzzy models as well as the reliability constraint.

(c) With respect to FRBESS, its computing efficiency may be improved by using fuzzy truth value inference instead of CRI. A fuzzy rule then is stated as "If X is high is true then Y is B is more or less true" where A and B are fuzzy values. Instead of compiling the fuzzy value A and B, a fuzzy truth value inference is to aggregate its truth value like 'true' and 'more or less true'. The truth value can be represented either in linguistic term, or as a single possibility value. This type of fuzzy inference system is a real type of production system, since the pattern "X is high" must first be matched exactly then the rule is hired. On contrast, in a CRI based fuzzy inference system all rules must be hired to participate an inference process. Therefore, the truth value based fuzzy inference system has the advantage by means of computing efficiency in comparison with CRI based fuzzy inference system.

REFERENCE

1. Adlassnig, K.P., Kolarz, G., Schweithauer, W., " Present state of the medical expert system CADIAG-2", *Methods of Information in Medicine*, Vol 24, pp13-20, 1985

2. Agraal, A., " A survey of network reliability ", *ORC -83-5*, Operation Research Centre, Berkeley, 1983.

3. Alexeyev,A.V., Borisov, A.N., *et al*, " A linguistic approach to decision-making problems", *Fuzzy Sets and Systems*, Vol 22, pp25-43, 1987.

4. ARINC Research Corporation, *Reliability Engineering*, Prentice-Hall Inc., 1964.

5. Bagowsky, I., *Reliability Theory and Practise*, Prentice-hall, 1961.

6. Bandler, W., Kohout, L.J., "Fuzzy implication operators", *Fuzzy Research Report FRP-21*, Department of Mathematics, University of Essex, 1983

7. Bell Communication Research TR-TRY-000332, *Reliability Prediction Procedure For Electronic Equipment*, 1986.

8. Bezdek, J.C., "Analysis of Fuzzy Information", *Application in Engineering and Science*, Vol III, CRC Press, 1987

9. Billinton, R., *Power System Reliability Evaluation* ,Gordon and Breach, USA, 1970.

10. Billinton, R., Allan, R.N., *Reliability Evaluation of Engineering Systems.* Longman Scientific &Technical, 1983.

11. Billinton, R., Allan, R.N., *Reliability Evaluation of Power Systems*, Pitman Publishing Ltd, 1984.

12. Cai, K.Y., Wen, C.Y., "Street-lighting lamps replacement: a fuzzy viewpoint", *Fuzzy Sets and Systems*, Vol 37, pp161-172, 1990

13. Calabrese, G., Generating reserve capacity determined by the probability methods, *IEE Transctions*, 66, pp1439-1450, 1947.

14. Chiles, D., "Workload, task, and situational factors as modifiers of complex Human performance", *Human Performance and Productivity,* Hillsdale, 1982.

15. Chui, D.K.H., " Artificial intelligence techniques for power system decision problems", *PhD Thesis*, University of London, 1988.

16. Chui, D.K.H., Laughton, M.A., "Power system control using fuzzy reasoning", *Proc. PSCC 10*, pp345-350, 1990.

17. Cooley, T.W., Hicks, T.O., "A fuzzy set approach to aggregating internal control judgement", *Management Science*, Vol 29 , pp317-334 , 1983.

18. Dellon, T.S., Laughton, M.A., *Expert System Application In Power Systems*, Prentice hall, 1990

19. Dubois, D., Prade, H., " Operations on fuzzy number", *Int. J. System Sci.*, Vol 9, pp613- 617, 1978.

20. Dubios, D., *Possibility Theory,* Plenum Press, New York, 1988.

21. Dubois, D., Prade, H., *Fuzzy Set and Systems: Theory and Application,* Academic Press, 1979

22. Dubois,D., Prade, H., " Fuzzy sets in approximate reasoning, part1: inference with possibility distributions", *Fuzzy Sets and Systems*, Vol 40, No. 1, pp143-202, March 5, 1991

23. Dubois,D., Prade, H., " Fuzzy sets in approximate reasoning, part2: logical approaches", *Fuzzy Sets and Systems*, Vol 40, No. 1, pp203-244, March 5, 1991.

24. Duda, R., Hart, P., Nilsson, N., "Subjective Bayesian methods for rule-based inference systems", *Proc. of AFIPS*, pp1075-1082, 1976

25. Duda, R., Hart, P., Barrett, P., "Development of the PROSPECTOR system for mineral exploration", *SRI Report Projects 5822 and 6415*, Stanford Researh Institute, 1978.

26. Erceg, M.A., " Functions, equivalence relations, quotient spaces & subsets in fuzzy set theory", *Fuzzy sets and Systems* , Vol 3, 1980.

27. Feagons, T.B., Biller, W.F., "Fuzzy concepts in the analysis of public health risks", *Fuzzy Sets*, pp. 391-404 , Plenum Press, New York, 1980.

28. Fieschi, M., Joubert, M., Fieschi, D., Rous, M., "SPHINX: a system for computer aided diagnosis", *Methods of Information in Medicine*, Vol 21, pp143-148, 1982

29. Ford, A., "Quantify uncertainty in energy model forcasts", *Energy Systems And Policy* , Vol 3, pp217-247, 1985.

30. Fukami, S., Mizumoto,M., Tanaka,K., "Some considerations on fuzzy condirional inference", *Fuzzy Sets and Systems*, Vol 4, pp243-273, 1980

31. Gaines, B.R., Shaw, M.L.G., " Foundations of expert systems", in: *Management Decision Support Systems Using Fuzzy Sets and Possibility Theory*, ISR, 1983

32. Garcia, J. P., Rios, J., Yague, J., "Methodology of linguistics evaluation in risk situations using fuzzy techniques", *Fuzzy Sets and Systems*, Vol 48, No 2, 1992.

33. Gote, G., Laughton, M.A., "Prediction of reserve requirements in generation planning". Electrical & Energy Systems, Vol 2, No 2, April 1980.

34. Gupta, M.M., Qi, J., " Theory of T-norms and fuzzy interface methods", *Fuzzy Sets and Systems*, Vol 40, No 3, pp 431-450, April 1991.

35. Gupta, M. M. and Qi, J., "Design of fuzzy logic controllers based on generalized T-operations", *Fuzzy Sets and Systems,* Vol 40 , No 3, pp473-491, April 1991.

36. Hoffman ,L.J., Michelman, E.H., "Security evaluation and analysis using fuzzy metrics", *Proceeding of The National Computer Conference,* Vol. 47, AFIPS Press, 1978.

37. Ireson, W.G. Combers, C.F., *Handbook of Reliability Engineering and Management.,* McGraw-Hill, 1988.

38. Jain, R., "Decision making in the presence of fuzziness and uncertainty ", *Proceeding of The 1977 IEEE Conference on Decision and Control,* pp1318-1323 , 1977.

39. Jones, P., "A model of organization dynamics", *Policy Evaluation Using REVEAL,* ICL ltd, 1985

40. Kandel, A.M.," Fuzzy statistic and forecast evaluation ", *IEE Transaction On Systems, Man And Cybernetics,* Vol. SMC-8, No 5, pp396-400, 1979.

41. Kandel, A., *Fuzzy Mathematical Techniques With Applications,* North Holland, Amsterdam, 1984.

42. Kaplan, E.L., "Nonparametric estimation from incomplete observation", *J. America Statistics Association,* Vol 53, pp457-481, 1985.

43. Karwowski, W., Mital, A., "Potential application of fuzzy sets in industrial Engineering", *Fuzzy Sets and Systems,* Vol 19, No 2, pp105-120 , June 1986.

44. Kaufman, A.D., *Mathematic Model For The Study Of The Reliability Of Systems,* Academic Press, 1977.

45. Kaufmann, A., *Introduction To The Theory Of Fuzzy Subsets,* Vol. 1, Academic Press, New York, 1979.

46. Kaufmann, A.D., Gupta, M.M., "Possibility theory in reliability modelling", *IAIOR*, Vol. 6, Interdisciplinary Systems Research Series, pp127-144 , 1989.

47. Kaufmann, A., Gupta M.M., *Fuzzy Mathematical Models In Engineering And Management Science*, Elsevier Science Publishers Company Inc., 1991.

48. Kevin Self, " Designing with fuzzy logic", *IEEE Spectrum*, pp42-44, November,1990

49. Kickert, W.J.M., Mamdani, E.H.M., "Analysis of fuzzy logic controller", *Fuzzy Sets and Systems*, Vol 1, pp29-44, 1978.

50. Klein, W.E., "Experience with modified aerospace reliability and quality assurance method for wind turbines", *Proceedings of the 1982 Engineering Conference For The Electric Power Industry*, pp. 232-237, 1982.

51. Laughton, M. A., "Fuzzy systems theory and its applications to power systems", *ESAP 93*, pp23-29, 1993 .

52. LeFaivre, R., " FUZZY: a programming language for fuzzy problem solving", *Technical Report 202*, Computer Science Dept., University of Wisconsin, 1974.

53. Luca, A. De, Termini, S., " Algebrian properties of fuzzy sets", *J. Math. Anal. Appl.*, Vol 29, 1972.

54. Mamdani, E.H., Gaines, B.R., *Fuzzy reasoning and its application*, Academic Press, 1981.

55. Martin-Clouaire, R., Prade, H., " SPII-1: a simple inference engine for accomdating both imprecision and uncertainty", *presented at Cognitive Conference*, Paris, 1984.

56. MIL-STD-785, *Reliability Program For System and Equipment Development and Production.*

67. Onisawa, T., "Fuzzy theory in analysis of system reliability", *Proc. of the 26th Society of Instrument and Control Engineering Annual Conference*, Vol 2, pp1257-1260, 1987.

68. Onisawa, T., "Reliability estimation from various subjective standpoints ", *Proc. of t he second IFSA Congress*, Vol 2, pp793-796, 1987.

69. Onisawa, T., "An approach to human reliability in man-machine systems using error possibility", *Fuzzy Sets and Systems*, Vol 27, No. 2, pp89-103, 1988.

70. Onisawa, T., "An application of fuzzy concepts to modelling of reliability anslysis", *Fuzzy Sets and Systems*, Vol 37, No 3, pp267-286 , 1990.

71. Onisawa, T., Nishiwaki, Y.,"Fuzzy human reliability analysis in the Chernobyl accident (case study)", *Fuzzy Sets and Systems,* Vol 2, No 2, pp115-128, November 1988.

72. Piskunov, A., "Fuzzy implication in fuzzy systems control", *Fuzzy Sets and Systems,* Vol 45, No 1, pp25-36, January 1992.

73. Reliability Test System Task Force of the IEE subcommittee on the Application of Probability Methods, "IEEE Reliability Test System", *IEEE Transactions*, PAS-98, pp2047-54, No.6, 1979.

74. Sanchez, E., "Resolution of composite fuzzy relation equations", *Information Control,* 54, pp38-48, 1972.

75. Science & Technology Comments, "The logic that dares not speak its name", *The Economist*, pp137-140, April 16th, 1994

57. Misra, K.B., Weber, G.C., "Use of fuzzy set theory for Level-I studies in probabilistic risk assessment", *Fuzzy Sets and Systems*, Vol 37, No 2, pp139-160, September, 1990.

58. Misra , K.B., Weber, G.C., " A new method for fuzzy fault tree analysis", *Microelectron and Reliability*, Vol 29, No 2, pp195-216, 1989.

59. Mizumoto, M., Tanaka, K., " Algebraic properties of fuzzy numbers", *International Conference of Cybernetics Society*, Washington DC, 1976.

60. Mizumoto, M., " Fuzzy reasoning methods by Zadel and Mamdani, and improved methods", *3rd Fuzzy Workshop on Fuzzy Reasoning -Theory and Application*, Queen Mary College, London, September, 1978.

61. Mizumoto, M., "Extended fuzzy reasoning", in:Gupta, M.M., *Approximate Fuzzy Reasoning*, North-Holland, Amsterdam, pp71-85, 1985.

62. Mizumoto,M., Zimmermann, H.J., "Comparision of fuzzy reasoning methods", *Fuzzy Sets and Systems,* Vol 8, pp253-283, 1982.

63. Negotia, C.V., Ralescu, D.A., *Application Of Fuzzy Sets To Systems Analysis*, Birkaeuser, Basel, 1978.

64. Nishiwaki, Y., "Possible application of fuzzy set theory to nuclear safety analysis, risk perception and nuclear plant siting evaluations", *Proceeding of International Workshop on Fuzzy Sets Applications*, pp213-231, Akademieverlag, Berlin,1986.

65. Nola, A.D., Sessa, S., *Fuzzy Relations And Their Applications To Knowledge Engineering*, Kluwer Academic Publishers, The Netherlands, 1989.

66. Noma, K., Tanaka, H., " On fault tree analysis with fuzzy probability", *Japanese J. of Ergonomics* , Vol 17, No 6, pp291-297, 1981

76. Seitz, T., Bovy, A., "Fuzzy sets in reliability analysis of power distribution systems", *ESAP* 93, pp212-217, 1993

77. Sembi, B., " Rule-based decision making using fuzzy sets in learning control systems", *PhD Thesis*, Queen Mary College, University of London, UK, 1980

78. Shortliffe, E., *Computer based medical consultation:MYCIN*, American Elsevier, New York, USA,1976.

79. Singer,D., "A fuzzy set approach to fault tree and reliability analysis", *Fuzzy Sets and Systems*, Vol 34, pp-145-155, 1990.

80. Sugeno, H.T. "Some mathematical tools for linguistic probability", *Fuzzy Sets and Systems*, Vol 2, No 1, 1979.

81. Sugeno, H.T., "A new approach based on fuzzy sets concepts to fault tree analysis and diagnosis of failure at nuclear power plants", *Proceeding of IAEA*, 1984.

82. Sullivan, W.G., " Decision analysis of capacity expansion strategies for electric Utilities, *IEEE Transaction of Engineering Management*, Vol 24 , No 4, pp139-144, 1980

83. Sullivan, R.L., *Power System Planning*, McGranw-Hill, USA, 1977.

84. Swan, A. D., Cuttman, H. E., *Handbook of Human Reliability Analysis with Emphasis On Nuclear Power Plant Application*, Sandia, 1983.

85. Symbolics, inc., "MACSYMA reference manual", *Symbolics inc.*, Computer Aided Mathematics Group, Burlington, Massachusetts, 1989

86. Symbolics, inc., "MACSYMA user's guide: annotated tutorials", *Symbolics inc.*, Computer Aided Mathematics Group, Burlington, Massachusetts, 1989

87. Terjersen, N.J., "Long Term Energy Demand Forecast", Queen Mary College, *Internal Report,* 1985.

88. Tomsovic, K., " Current status of fuzzy set theory applications to power system", *to appeal in JIEE,* 1993

89. Wang , P.Z., *Theory of Fuzzy Sets and Its Application(in Chinese),* Shanghai Science and Technology Press, 1983.

90. Weiss, S., Kulikowski, C., *A practical Guide to designing expert systems,* Methuen, New York, 1983.

91. Yager, R.R., "Paths of least resistance in possibilistic production systems", *Fuzzy Sets and Systems,* Vol 19, No 2, pp121-132, 1986.

92. Zadeh, L.A., "Fuzzy Sets", *Information and Control,* 8, pp338-353, 1965.

93. Zadeh, L.A., "Towards a theory of fuzzy system", in: *Aspects of Networks and Systems Theory,* Kalman (eds), Rhinehart and Winston, 1971.

94. Zadel, L.A., " Outline of a new approach to the analysis of complex systems and decision process", *IEEE Trans. Systems Man Cybernet.,* Vol 3, pp28-44, 1973.

95. Zadel, L.A., Fu,K.S., Tanaka,K., Shimura, M., *Fuzzy sets and their applications to cognitive and decision process,* Academic Press, 1975.

96. Zadel, L.A., "Fuzzy logic and approximatie reasoning", *Synthese,* 30, pp407-428,1975

97. Zadel, L.A., "The concept of linguistic variables and its applications to approximate reasoning part I,II,III", *Information Science,* 8, pp43-80, pp199-248, pp301-357, 1975.

98. Zadel, L.A., " A theory of approximate reasoning", *Memo No. M77/58,* Electronics Research Laboratorey, University of California, 1977

99. Zadel, L.A., "Inference in fuzzy logic", *Proceeding of IEEE*, pp124-131, 1980

100. Zadeh, L.A., " Similarity relations and fuzzy orderings", *Information Science 3*, 1971.

101. Zadeh, L.A., "PRUF- a meaning representation language for natural languages", *Int. J. of Man-machine Studies*, Vol 10, No 4, pp395-460, 1978

Appendix I

Fuzzy Sets & Fuzzy Reasoning Operations Defined In FRBESS

A.I-1. Fuzzy Sets Primitive Operators

Intersection:

$$\mu_{A \cap B}(x) = \mu_A(x) \wedge \mu_B(x)$$

where $\wedge$ denotes MIN operation.

Union:

$$\mu_{A \cup B}(x) = \mu_A(x) \vee \mu_B(x)$$

where $\vee$ denotes MAX operation.

Complementation:

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

Product:

$$\mu_{A*B}(x) = \mu_A(x) \times \mu_B(x)$$

Normalisation:

$$\text{Norm}(A) = \frac{\mu_A(x)}{\mu_{A'}(x)}$$

where $\mu_{A'}(x) = \sup(\mu_A(x))$

Concentration:

$$\mu_{CON(A)}(x) = \mu_A{}^2(x)$$

Dilation:

$$\mu_{DIL(A)}(x) = \mu_A{}^{0.5}(x)$$

Intensification:

$$\mu_{INT(A)}(x) = \mu_A{}^{0.5}(x) \qquad \text{if } \mu_A(x) >= 0.5$$

$$\mu_{INT(A)}(x) = \mu_A{}^2(x) \qquad \text{if } \mu_A(x) < 0.5$$

A.I-2 Fuzzy Connectives

Conjunction:

Alias "AND" Operation: A AND B $\Rightarrow$ MIN (A, B)

Disjunction:

Alias "OR" Operation: A OR B $\Rightarrow$ MAX(A,B)

A.I-3 Fuzzy Hedge Operators

Shift Operators

more_than(A) $:=\mu_A(x+a)$

less_than(A)	$:=\mu_A(x-a)$	
between(A,B)	$:=\mu_A(x)$	if $x<=a$ where $\mu_A(a)=1$
	$:=1$	if $a<x<=b$ where $\mu_B(b)=1$
	$:=\mu_B(x)$	if $x>b$

Power Operators:

very(A)	$:=\mu_A^2(x)$	
more_or_less(A)	$:=\mu_A^{0.5}(x)$	

more_or_less(A)=fairly(A)=much(A)

above(A)	$:=1-\mu_A(x)$	if $x<0.5$
	$:=0$	if $x>0.5$
below(A)	$:=1-\mu_A(x)$	if $x>0.5$
	$:=0$	if $x<0.5$
not(A)	:=complement(A)	
indeed(A)	:=2*very(A)	if $x<=0.5$

	:=1-(2*very(not(A)))	if x>0.5
quite(A)	:=2*very(very(A))	if x<=0.5
	:=1-(2*very(1-very(A)))	if x>0.5
plus(A)	:=$\mu_A^{1.25}(x)$	
minus(A)	:=$\mu_A^{0.75}(x)$	
extremely(A)	:=$\mu_A^{3}(x)$	
highly(A)	:=plus(very(A))	
slightly(A)	:=INT(MORM(plus(A) AND (not(very(A)))))	
pretty(A)	:=NORM(indeed(very(A)) AND indeed(A))	
rather(A)	:=NORM(indeed(very(a)) AND very(A))	
sort_of(A)	:=NORM(not(very(very(A)) AND more_or_less(A))	

alias(very, much)

alias(more_or_less, fairly)

Appendix II

IEEE Reliability Test System(RTS)

A1. General Data

Total Installed Capacity=3405 MW.

Study load period=364 days=8736 hours.

Annual peak load=2850 MW.

Annual Load Factor=61.4%.

A2. Generating Unit Reliability Data

Table A1.4 - Generating unit reliability data

Unit size MW	Number of units	Forced outage rate	MTTF hr	MTTR hr	Scheduled maintenance wk/yr
12	5	0.02	2940	60	2
20	4	0.10	450	50	2
50	6	0.01	1980	20	2
76	4	0.02	1960	40	3
100	3	0.04	1200	50	3
155	4	0.04	960	40	4
197	3	0.05	950	50	4
350	1	0.08	1150	100	5
400	2	0.12	1100	150	6

A3. Load Data

Table A1.2 - Daily peak load in percent of weekly peak

Day	Peak load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Table A1.1 – Weekly peak load in percent of annual peak

Week	Peak load	Week	Peak load
1	86.2	27	75.5
2	90.0	28	81.6
3	87.8	29	80.1
4	83.4	30	88.0
5	88.0	31	72.2
6	84.1	32	77.6
7	83.2	33	80.0
8	80.6	34	72.9
9	74.0	35	72.6
10	73.7	36	70.5
11	71.5	37	78.0
12	72.7	38	69.5
13	70.4	39	72.4
14	75.0	40	72.4
15	72.1	41	74.3
16	80.0	42	74.4
17	75.4	43	80.0
18	83.7	44	88.1
19	87.0	45	88.5
20	88.0	46	90.9
21	85.6	47	94.0
22	81.1	48	89.0
23	90.0	49	94.2
24	88.7	50	97.0
25	89.6	51	100.0
26	86.1	52	95.2

Table A1.3 – Hourly peak load in percent of daily peak

	Winter weeks 1-8 & 44-52		Summer weeks 18 – 30		Spring/Fall weeks 9-17 & 31-43	
Hour	Wkdy	Wknd	Wkdy	Wknd	Wkdy	Wknd
12-1 am	67	78	64	74	63	75
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66
4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	95	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-Noon	95	91	100	93	99	94
Noon-1 pm	95	90	99	93	93	91
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

Wkdy = Weekday, Wknd = Weekend

APPENDIX III

Fuzzy Device Reliability Prediction Rules For Chapter 3 Case Studies

```
/**** the ruleset  for predicting device total failure possibility of the test unit ****/

RB_FAILURE:[

/* ruleset for determining the_failure_possibility of (device_(x))*/

['the_failure_possibility,

 [rule1,

        [[con,   [' internal_stress, ' the_comparative_influence, 'normal],

                 [' external_stress,  'the_comparative_influence, 'normal],

                 ['device_(x), ' the_basic_failure_estimation, 'high]],

        ['device_(x), ' the_failure_possibility, 'high]]],

 [rule2,

        [[con,   [' internal_stress, ' the_comparative_influence, 'normal],

                 [' external_stress,  'the_comparative_influence, 'normal],

                 [' device_(x), ' the_basic_failure_estimation, 'moderate]],

        ['device_(x), ' the_failure_possibility, 'moderate]]],

 [rule3,

        [[con,   [' internal_stress, ' the_comparative_influence, 'normal],

                 [' external_stress,  'the_comparative_influence, 'normal],

                 ['device_(x), ' the_basic_failure_estimation,'low]],

        ['device_(x), ' the_failure_possibility, 'low]]],

 [rule4,

        [[con,   [' internal_stress, ' the_comparative_influence, 'normal],
```

```
                ['external_stress, 'the_comparative_influence, 'positive_strong],
                ['device_(x), ' the_basic_failure_estimation, 'high]],
          ['device_(x), ' the_failure_possibility, 'high]]],
[rule5,
          [[con,    [' internal_stress, ' the_comparative_influence, 'normal],
                    [' external_stress, 'the_comparative_influence, 'positive_weak],
                    ['device_(x), ' the_basic_failure_estimation,'high]],
          ['device_(x), ' the_failure_possibility, 'less_than(high)]]],

[rule6,
          [[con,    [' internal_stress, ' the_comparative_influence, 'positive_strong],
                    [' external_stress, 'the_comparative_influence, 'normal],
                    ['device_(x), ' the_basic_failure_estimation,'high]],
          ['device_(x), ' the_failure_possibility, 'high]]],
[rule7,
          [[con,    [' internal_stress, ' the_comparative_influence, 'positive_weak],
                    [' external_stress, 'the_comparative_influence, 'normal],
                    ['device_(x), ' the_basic_failure_estimation,'high]],
          ['device_(x), ' the_failure_possibility, 'less_than(high)]]],
[rule8,
          [[con,    [' internal_stress, ' the_comparative_influence, 'nagetive_weak],
                    [' external_stress, 'the_comparative_influence, 'normal],
                    ['device_(x), ' the_basic_failure_estimation,'high]],
          ['device_(x), ' the_failure_possibility, 'more_than(moderate)]]],
```

```
[rule9,
        [[con,  [' internal_stress, ' the_comparative_influence, 'nagetive_strong],
                [' external_stress,  'the_comparative_influence, 'normal],
                ['device_(x), ' the_basic_failure_estimation,'moderate]],
        ['device_(x), ' the_failure_possibility, 'low]]],
[rule10,
        [[con,  [' internal_stress, ' the_comparative_influence, 'normal],
                [' external_stress,  'the_comparative_influence, 'nagetive_weak],
                ['device_(x), ' the_basic_failure_estimation,'high]],
        ['device_(x), ' the_failure_possibility, 'more_than(moderate)]]],
[rule11,
        [[con,  [' internal_stress, ' the_comparative_influence, 'positive_weak],
                [' external_stress,  'the_comparative_influence, 'nagetive_weak],
                ['device_(x), ' the_basic_failure_estimation,'moderate]],
        ['device_(x), ' the_failure_possibility, 'moderate]]],
[rule12,
        [[con,  [' internal_stress, ' the_comparative_influence, 'nagetive_weak],
                [' external_stress,  'the_comparative_influence, 'positive_weak],
                ['device_(x), ' the_basic_failure_estimation,'low]],
        ['device_(x), ' the_failure_possibility, 'low]]]],
/* ruleset for determining internal_stress*/
['internal_stress,
[rule1,
        [[con,  ['electric_defect, ' the_comparative_influence,'normal],
```

```
                ['thermal_defect, ' the_comparative_influence, 'normal]],
            ['internal_stress,' the_comparative_influence, 'normal]]],
 [rule2,
            [[con,   ['electric_defect, ' the_comparative_influence,'positive_strong],
                     ['thermal_defect, ' the_comparative_influence, 'positive_strong]],
            ['internal_stress,' the_comparative_influence, 'less_than(positive_strong)]]],
 [rule3,
            [[con,   ['electric_defect, ' the_comparative_influence,'positive_strong],
                     ['thermal_defect, ' the_comparative_influence, 'positive_weak]],
            ['internal_stress,' the_comparative_influence, 'more_than(positive_weak)]],
 [rule4,
            [[con,   ['electric_defect, ' the_comparative_influence,'positive_weak],
                     ['thermal_defect, ' the_comparative_influence, 'positive_weak]],
            ['internal_stress,' the_comparative_influence, 'more_than(positive_weak)]]],
 [rule5,
            [[con,   ['electric_defect, ' the_comparative_influence,'nagetive_weak],
                     ['thermal_defect, ' the_comparative_influence, 'positive_weak]],
            ['internal_stress,' the_comparative_influence, 'normal]]],
 [rule6,
            [[con,   ['electric_defect, ' the_comparative_influence,'positive_weak],
                     ['thermal_defect, ' the_comparative_influence, 'nagetive_weak]],
            ['internal_stress,' the_comparative_influence, 'normal]]],
 [rule7,
            [[con,   ['electric_defect, ' the_comparative_influence,'normal],
```

```
                ['thermal_defect, ' the_comparative_influence, 'normal]],
          ['internal_stress,' the_comparative_influence, 'normal]]],
 [rule8,
          [[con,   ['electric_defect, ' the_comparative_influence,'normal],
                   ['thermal_defect, ' the_comparative_influence, 'nagetive_strong]],
          ['internal_stress,' the_comparative_influence, 'more_than(nagetive_weak)]]]],
 /* ruleset for determining external stress*/
 ['external_stress,
 [rule1,
          [[con,   ['variance_of_weather, ' the_comparative_influence,'normal],
                   ['variance_of_maintenance,'the_comparative_influence,'normal]],
          ['external_stress,' the_comparative_influence,'normal]]],
 [rule2,
          [[con,   ['variance_of_weather, ' the_comparative_influence,'positive_weak],
                   ['variance_of_maintenance,'the_comparative_influence,'nagetive_weak]],
          ['external_stress,' the_comparative_influence,'normal]]],
 [rule3,
          [[con,   ['variance_of_weather, ' the_comparative_influence,'positive_weak],
                   ['variance_of_maintenance,'the_comparative_influence,'normal]],
          ['external_stress,' the_comparative_influence,'less_than(positive_weak)]]],
 [rule4,
          [[con,   ['variance_of_weather,'the_comparative_influence,'positive_strong],
                   ['variance_of_maintenance,'the_comparative_influence,'nagetive_weak]],
          ['external_stress,' the_comparative_influence,'more_than(normal)]]],
```

```
[rule5,
        [[con,  ['variance_of_weather,'the_comparative_influence,'positive_strong],
                ['variance_of_maintenance,'the_comparative_influence,'normal]],
        ['external_stress,' the_comparative_influence,'less_than(positive_weak)]]]],
]$


/***rulesets  for predicting maintenance time of the test unit ***/
RB_MAINTENANCE:[
/* ruleset for determining the_total_maintenance_time of device_(x) */
['the_total_maintenance_time,
[rule1,
        [[con,  ['active_maintenance, ' the_comparative_influence,'normal],
                ['maintenance_administration,' the_comparative_influence,'normal],
                ['device_(x), 'the_basic_maintenance_estimation, 'between_medium_and_long]],
        ['device_(x),'the_total_maintenance_time, 'between_medium_and_long]]],
[rule2,
        [[con,  ['active_maintenance, ' the_comparative_influence,'normal],
                ['maintenance_administration,' the_comparative_influence,'normal],
                ['device_(x), 'the_basic_maintenance_estimation, 'medium]],
        ['device_(x),'the_total_maintenance_time, 'medium]]],
[rule3,
        [[con,  ['active_maintenance, ' the_comparative_influence,'normal],
                ['maintenance_administration,' the_comparative_influence,'positive_weak],
                ['device_(x), 'the_basic_maintenance_estimation, 'medium]],
```

```
['device_(x),'the_total_maintenance_time,'more_than(more_than(between_medium_and_long))]

[rule4,

    [[con,  ['active_maintenance, ' the_comparative_influence,'positive_weak],

            ['maintenance_administration,' the_comparative_influence,'normal],

            ['device_(x), 'the_basic_maintenance_estimation, 'medium]],

    ['device_(x),'the_total_maintenance_time,'more_than(more_than(between_medium_and_long))]

[rule5,

    [[con,  ['active_maintenance, ' the_comparative_influence,'positive_weak],

            ['maintenance_administration,' the_comparative_influence,'positive_weak],

            ['device_(x), 'the_basic_maintenance_estimation, 'between_medium_and_long]],

    ['device_(x),'the_total_maintenance_time, 'longest]]],

[rule6,

    [[con,  ['active_maintenance, ' the_comparative_influence,'positive_weak],

            ['maintenance_administration,' the_comparative_influence,'positive_weak],

            ['device_(x), 'the_basic_maintenance_estimation, 'medium]],

    ['device_(x),'the_total_maintenance_time, 'longest]]],

[rule7,

    [[con,  ['active_maintenance, ' the_comparative_influence,'normal],

            ['maintenance_administration,' the_comparative_influence,'positive_weak],

            ['device_(x), 'the_basic_maintenance_estimation, 'between_medium_and_long]],

    ['device_(x),'the_total_maintenance_time, 'longest]]],

[rule8,

    [[con,  ['active_maintenance, ' the_comparative_influence,'positive_weak],

            ['maintenance_administration,' the_comparative_influence,'normal],
```

```
['device_(x), 'the_basic_maintenance_estimation, 'between_medium_and_long]],
['device_(x),'the_total_maintenance_time, 'longest]]],
[rule9,
[[con, ['active_maintenance, ' the_comparative_influence,'nagetive_weak],
['maintenance_administration,' the_comparative_influence,'positive_weak],
['device_(x), 'the_basic_maintenance_estimation, 'long]],
['device_(x),'the_total_maintenance_time, 'long]]],
[rule10,
[[con, ['active_maintenance, ' the_comparative_influence,'nagetive_weak],
['maintenance_administration,' the_comparative_influence,'positive_weak],
['device_(x), 'the_basic_maintenance_estimation, 'medium]],
['device_(x),'the_total_maintenance_time, 'medium]]],
[rule11,
[[con, ['active_maintenance, ' the_comparative_influence,'nagetive_weak],
['maintenance_administration,' the_comparative_influence,'positive_weak],
['device_(x), 'the_basic_maintenance_estimation, 'short]],
['device_(x),'the_total_maintenance_time, 'short]]],
/* ruleset for determining active_maintenance */
['active_maintenance,
[rule1,
[[con, ['fault_detection,'the_comparative_influence,'normal],
['removal&fix&installation,'the_comparative_influence,'normal],
['preparation,'the_comparative_influence,'normal]],
['active_maintenance,'the_comparative_influence,'normal]]],
```

```
[rule2,
    [[con, ['fault_detection,'the_comparative_influence,'positive_weak],
           ['removal&fix&installation,'the_comparative_influence,'positive_weak],
           ['preparation,'the_comparative_influence,'nagetive_weak]],
    ['active_maintenance,'the_comparative_influence,'between(normal,positive_weak)]]],
[rule3,
    [[con, ['fault_detection,'the_comparative_influence,'positive_weak],
           ['removal&fix&installation,'the_comparative_influence,'positive_weak],
           ['preparation,'the_comparative_influence,'normal]],
    ['active_maintenance,'the_comparative_influence,'less_than(positive_weak)]]],
[rule4,
    [[con, ['fault_detection,'the_comparative_influence,'positive_strong],
           ['removal&fix&installation,'the_comparative_influence,'positive_weak],
           ['preparation,'the_comparative_influence,'normal]],
    ['active_maintenance,'the_comparative_influence,'more_than(positive_weak)]]],
[rule5,
    [[con, ['fault_detection,'the_comparative_influence,'positive_strong],
           ['removal&fix&installation,'the_comparative_influence,'positive_weak],
           ['preparation,'the_comparative_influence,'nagetive_weak]],
    ['active_maintenance,'the_comparative_influence,'between(positive_weak,positive_strong)]]],
[rule6,
    [[con, ['fault_detection,'the_comparative_influence,'normal],
           ['removal&fix&installation,'the_comparative_influence,'positive_weak],
           ['preparation,'the_comparative_influence,'nagetive_weak]],
```

```
        ['active_maintenance,'the_comparative_influence,'normal]]],
 [rule7,
        [[con,  ['fault_detection,'the_comparative_influence,'nagetive_weak],
                ['removal&fix&installation,'the_comparative_influence,'normal],
                ['preparation,'the_comparative_influence,'positive_weak]],
        ['active_maintenance,'the_comparative_influence,'normal]]],
/* ruleset for determining maintenance_administration */
['maintenance_administration,
 [rule1,
        [[con,  ['maintenancer_training,'the_comparative_influence,'normal],
                ['part_stock_planning,'the_comparative_influence,'normal]],
        ['maintenance_admimistration,'the_comparative_influence,'normal]]],
 [rule2,
        [[con,  ['maintenancer_training,'the_comparative_influence,'normal],
                ['part_stock_planning,'the_comparative_influence,'positive_weak]],
        ['maintenance_admimistration,'the_comparative_influence,'between(normal,nagetive_weak)]]],
 [rule3,
        [[con,  ['maintenancer_training,'the_comparative_influence,'nagetive_weak],
                ['part_stock_planning,'the_comparative_influence,'positive_weak]],
        ['maintenance_admimistration,'the_comparative_influence,'normal]]],
 [rule4,
        [[con,  ['maintenancer_training,'the_comparative_influence,'nagetive_weak],
                ['part_stock_planning,'the_comparative_influence,'normal]],
        ['maintenance_admimistration,'the_comparative_influence,'between(normal,nagetive_weak)]]],
```

```
[rule5,

        [[con,  ['maintenancer_training,'the_comparative_influence,'positive_strong],

                ['part_stock_planning,'the_comparative_influence,'nagetive_strong]],

        ['maintenance_admimistration,'the_comparative_influence,'normal]]]]

]$



/**** the rulesets for predicting human error possibility of the test unit ****/

RB_ERROR:[

/* ruleset for determining the_human_error_possibility */

['the_human_error_possibility,

[rule1,

        [[con,  ['mental&congnitive_stress,' the_comparative_influence,'normal],

                ['environmental_stress,'the_comparative_influence,'normal],

                ['device_(x),'the_basic_error_estimation,'moderate]],

        ['device_(x),'the_human_error_possibility,'moderate]]],

[rule2,

        [[con,  ['mental&congnitive_stress,' the_comparative_influence,'normal],

                ['environmental_stress,'the_comparative_influence,'positive_weak],

                ['device_(x),'the_basic_error_estimation,'moderate]],

        ['device_(x),'the_human_error_possibility,'between(high,between_moderate_and_high)]]],

[rule3,

        [[con,  ['mental&congnitive_stress,' the_comparative_influence,'nagetive_weak],

                ['environmental_stress,'the_comparative_influence,'normal],

                ['device_(x),'the_basic_error_estimation,'moderate]],
```

```
        ['device_(x),'the_human_error_possibility,'between(low,between_low_and_moderate)]]],
 [rule4,
        [[con,  ['mental&congnitive_stress,' the_comparative_influence,'nagetive_weak],
                ['environmental_stress,'the_comparative_influence,'positive_weak],
                ['device_(x),'the_basic_error_estimation,'moderate]],
        ['device_(x),'the_human_error_possibility,'moderate]]],
 [rule5,
        [[con,  ['mental&congnitive_stress,' the_comparative_influence,'positive_weak],
                ['environmental_stress,'the_comparative_influence,'positive_weak],
                ['device_(x),'the_basic_error_estimation,'low]],
        ['device_(x),'the_human_error_possibility,'between(moderate,between_moderate_and_high)]]],
/* ruleset for determining mental&cognitive_stress */
['mental&congnitive_stress,
[rule1,
        [[con,  ['competence,'the_comparative_influence,'normal],
                ['phychological_stress,'the_comparative_influence,'normal]],
        ['mental&congnitive_stress,'the_comparative_influence,'normal]]],
[rule2,
        [[con,  ['competence,'the_comparative_influence,'nagetive_weak],
                ['phychological_stress,'the_comparative_influence,'normal]],
        ['mental&congnitive_stress,'the_comparative_influence,'between(nagetive,normal)]]],
[rule3,
        [[con,  ['competence,'the_comparative_influence,'nagetive_weak],
                ['phychological_stress,'the_comparative_influence,'positive_weak]],
```

```
        ['mental&congnitive_stress,'the_comparative_influence,'normal]]],

/* ruleset for determining environmental stress */

['environmental_stress,

[rule1,

        [[con,  ['workload,' the_comparative_influence,'normal],

                ['weather,'the_comparative_influence,'normal]],

        ['environmental_stress,'the_comparative_influence,'normal]]],

[rule2,

        [[con,  ['workload,' the_comparative_influence,'positive_weak],

                ['weather,'the_comparative_influence,'positive_weak]],

        ['environmental_stress,'the_comparative_influence,'less_than(positive_weak)]]],

[rule3,

        [[con,  ['workload,' the_comparative_influence,'positive_weak],

                ['weather,'the_comparative_influence,'positive_strong]],

        ['environmental_stress,'the_comparative_influence,'more_than(positive_weak)]]],

[rule4,

        [[con,  ['workload,' the_comparative_influence,'positive_strong],

                ['weather,'the_comparative_influence,'positive_weak]],

        ['environmental_stress,'the_comparative_influence,'more_than(positive_weak)]]],

[rule5,

        [[con,  ['workload,' the_comparative_influence,'positive_strong],

                ['weather,'the_comparative_influence,'positive_strong]],

        ['environmental_stress,'the_comparative_influence,'positive_strong]]]]

]$
```

/*** the data sets for the test unit,reliability prediction***/

/*** it contains the definition for fuzzy terms and the universe of discourses ***/

/* S and P fuzzy number definition */

S(x,a,b,c):=if x<=a then 0 else if (x>a and x<=b) then 2*((x-a)/(c-a))**2 else if (x>b and <=c) then 1$

P(x,d,e):= if x<=e then s(x,e-d, e-d/2,e) else if x>e then 1-s(x,e, e+d/2, e+d)$

/* the definition for the universe of discourses */

f(x):=m*log(x)+n$

g(x):=10 exp((x-n)/m) $

(m: 5, n: 25, the_total_failure_possibility:make_discourse(f(10exp(-5)), f(10exp(-3))),
the_human_error_possibility: make_discourse(f(10exp(-5)), f(10exp(-3))) $

(m:0,n:5,the_total_maintenance_time: make_discourse(f(10exp(0)), f(10exp(2))) $

/* fuzzy terms definition , fuzzy subsets are defined as 11 levels discrete set. The functions "make_S_distribution" and "make_P_distribution" are for transferring P and S types fuzzy number to the set of X=[0,1,2,3,4,5,6,7,8,9,10] */

lowest: make_S_distribution(0,10,2,0.5,0)$

low: make_S_distribution(0,10,3,1.5,0)$

between_low_and_moderate:make_P_distribution(0,10,3,3) $

moderate: make_P_distribution(0,10,3,5) $

between_moderate_to_high: make_P_distribution(0,10,3,7) $

high: make_S_distribution(0,10,7,8.5,10) $

highest: make_S_distribution(0,10, 8, 9.5, 10) $

shortest: make_S_distribution(0,10,2,0.5,0)$

short: make_S_distribution(0,10,3,1.5,0)$

between_short_and_medium:make_P_distribution(0,10,3,3) $

medium: make_P_distribution(0,10,3,5) $

between_medium_to_long: make_P_distribution(0,10,3,7) $

long: make_S_distribution(0,10,7,8.5,10) $

longest: make_S_distribution(0,10, 8, 9.5, 10) $

positive_strong: make_S_distribution(-5,5,2,3.5,5) $

positive_weak: make_P_distribution(-5,5, 3, 3) $

normal: make_P_distribution(-5,5,3 ,0) $

nagetive_weak: make_P_distribution(-5,5,3 ,-3) $

nagetive_strong: make_S_distribution(-5,5, -2, -3.5, -5) $

/* special terms set */

any: [1,1,1,1,1,1,1,1,1,1,1] $

unknown: [0,0,0,0,0,0,0,0,0,0,0] $

Appendix IV

Fuzzy System Reliability Combination Rules For Ch4 Case Studies

```
/**** The rulesets for combining system reliability ****/

RB_Combination_Survive:[

/* ruleset for initial system combination */

['initial_combination,

    [rule1,

        [[con,  ['the_current_system, 'survive_possibility,'any],

                ['the_adding_unit_(X), 'survive_possibility, 'certain]],

        [' the_current_system, 'survive_possibility,'certain]]],

    [rule2,

        [[con,  ['the_current_system, 'survive_possibility,'any],

                ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],

        [' the_current_system, 'survive_possibility,'almost_certain]]],

    [rule3,

        [[con,  ['the_current_system, 'survive_possibility,'any],

                ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],

        [' the_current_system, 'survive_possibility,'quite_possible]]],

    [rule4,

        [[con,  ['the_current_system, 'survive_possibility,'any],

                ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],

        [' the_current_system, 'survive_possibility,'moderate_possible]]],

    [rule5,
```

```
            [[con,   ['the_current_system, 'survive_possibility,'any],
                     ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
            [' the_current_system, 'survive_possibility,'slightly_possible]]],
    [rule6,
            [[con,   ['the_current_system, 'survive_possibility,'any],
                     ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
            [' the_current_system, 'survive_possibility,'almost_impossible]]],
    [rule7,
            [[con,   ['the_current_system, 'survive_possibility,'any],
                     ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
            [' the_current_system, 'survive_possibility,'impossible]]]],
/* ruleset for series_connected units combination */
[series_connection,
    [rule1,
            [[con,   ['the_current_system, 'survive_possibility, 'certain],
                     ['the_adding_unit_(X), 'survive_possibility, 'certain]],
            [' the_current_system, 'survive_possibility, 'certain]]],
    [rule2,
            [[con,   ['the_current_system, 'survive_possibility, 'certain],
                     ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
            [' the_current_system, 'survive_possibility,'almost_certain]]],
    [rule3,
            [[con,   ['the_current_system, 'survive_possibility, 'certain],
                     ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
```

```
        [' the_current_system, 'survive_possibility,'quite_possible]]],
[rule4,
        [[con,  ['the_current_system, 'survive_possibility, 'certain],
                ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
        [' the_current_system, 'survive_possibility,'moderate_possible]]],
[rule5,
        [[con,  ['the_current_system, 'survive_possibility, 'certain],
                ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
        [' the_current_system, 'survive_possibility,'slightly_possible]]],
[rule6,
        [[con,  ['the_current_system, 'survive_possibility, 'certain],
                ['the_adding_unit_(X), 'survive_possibility,'almost_impossible]],
        [' the_current_system, 'survive_possibility,' almost_impossible]]],
[rule7,
        [[con,  ['the_current_system, 'survive_possibility,  'certain],
                ['the_adding_unit_(X), 'survive_possibility,'impossible]],
        [' the_current_system, 'survive_possibility,'impossible]]],
[rule8,
        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
                ['the_adding_unit_(X), 'survive_possibility,'certain]],
        [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule9,
        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
                ['the_adding_unit_(X), 'survive_possibility,'almost_certain]],
```

```
        [' the_current_system, 'survive_possibility, 'less_than(almost_certain)]]],

    [rule10,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],

                ['the_adding_unit_(X), 'survive_possibility,'quite_possible]],

        [' the_current_system, 'survive_possibility, 'less_than(quite_possible)]]],

    [rule11,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],

                ['the_adding_unit_(X), 'survive_possibility,'moderate_possible]],

        [' the_current_system, 'survive_possibility,  'less_than(moderate_possible)]]],

    [rule12,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],

                ['the_adding_unit_(X), 'survive_possibility,'slightly_possible]],

        [' the_current_system, 'survive_possibility,  'less_than(slightly_possible)]]],

    [rule13,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],

                ['the_adding_unit_(X), 'survive_possibility,'almost_impossible]],

        [' the_current_system, 'survive_possibility, 'less_than(almost_impossible)]]],

    [rule14,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],

                ['the_adding_unit_(X), 'survive_possibility,'impossible]],

        [' the_current_system, 'survive_possibility, 'less_than(impossible)]]],

    [rule15,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'certain]],
```

```
        [' the_current_system, 'survive_possibility, 'quite_possible]]],

[rule16,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'almost_certain]],

        [' the_current_system, 'survive_possibility, 'less_than(quite_possible)]]],

[rule17,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'quite_possible]],

        [' the_current_system, 'survive_possibility, 'less_than(moderate_possible)]]],

[rule18,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'moderate_possible]],

        [' the_current_system, 'survive_possibility, 'less_than(slightly_possible)]]],

[rule19,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'slightly_possible]],

        [' the_current_system, 'survive_possibility,  'less_than(almost_impossible)]]],

[rule20,

        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],

                ['the_adding_unit_(X), 'survive_possibility,'almost_impossible]],

        [' the_current_system, 'survive_possibility,  'less_than(impossible)]]],

[rule21,

        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],

                ['the_adding_unit_(X), 'survive_possibility, 'certain]],
```

```
        [' the_current_system, 'survive_possibility, 'moderate_possible]]],

[rule22,

        [[con,   ['the_current_system, 'survive_possibility, 'moderate_possible],

                 ['the_adding_unit_(X), 'survive_possibility,'almost_certain]],

        [' the_current_system, 'survive_possibility, 'less_than(moderate_possible)]]],

[rule23,

        [[con,   ['the_current_system, 'survive_possibility, 'moderate_possible],

                 ['the_adding_unit_(X), 'survive_possibility,'quite_possible]],

        [' the_current_system, 'survive_possibility, 'less_than(slightly_possible]]],

[rule24,

        [[con,   ['the_current_system, 'survive_possibility, 'moderate_possible],

                 ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],

        [' the_current_system, 'survive_possibility, 'impossible]]],

[rule25,

        [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],

                 ['the_adding_unit_(X), 'survive_possibility,'certain]],

        [' the_current_system, 'survive_possibility, 'slightly_possible]]],

[rule26,

        [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],

                 ['the_adding_unit_(X), 'survive_possibility,'almost_certain]],

        [' the_current_system, 'survive_possibility, 'less_than(slightly_possible]]],

[rule27,

        [[con,   ['the_current_system, 'survive_possibility,'slightly_possible],

                 ['the_adding_unit_(X), 'survive_possibility,'quite_possible]],
```

```
        [' the_current_system, 'survive_possibility,'less_than(impossible)]]],

    [rule28,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],

                ['the_adding_unit_(X), 'survive_possibility,'certain]],

        [' the_current_system, 'survive_possibility,'almost_impossible]]],

    [rule29,

        [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],

                ['the_adding_unit_(X), 'survive_possibility,'almost_certain]],

        [' the_current_system, 'survive_possibility,'less_than(impossible)]]],

    [rule30,

        [[con,  ['the_current_system, 'survive_possibility, 'impossible],

                ['the_adding_unit_(X), 'survive_possibility,'certain]],

        [' the_current_system, 'survive_possibility,'impossible]]],

    [rule31,

        [[con,  ['the_current_system, 'survive_possibility, 'impossible],

                ['the_adding_unit_(X), 'survive_possibility,' almost_certain]],

        [' the_current_system, 'survive_possibility, 'very(less_than(impossible))]]]],

/* ruleset for parallel connected units combination */

[parallel_connection,

    [rule1,

        [[con,  ['the_current_system, 'survive_possibility, 'certain],

                ['the_adding_unit_(X), 'survive_possibility, 'certain]],

        [' the_current_system, 'survive_possibility, 'more_than(very(certain))]]],

    [rule2,
```

```
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
            [' the_current_system, 'survive_possibility, ' very(certain)]]],
    [rule3,
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
            [' the_current_system, 'survive_possibility, 'certain]]],
    [rule4,
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
            [' the_current_system, 'survive_possibility, 'certain]]],
    [rule5,
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
            [' the_current_system, 'survive_possibility, 'certain]]],


    [rule6,
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
            [' the_current_system, 'survive_possibility, ' certain]]],
    [rule7,
            [[con,  ['the_current_system, 'survive_possibility, 'certain],
                    ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
            [' the_current_system, 'survive_possibility, 'certain]]],
```

```
[rule8,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'certain]],
    [' the_current_system, 'survive_possibility, 'very(certain)]]],
[rule9,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
    [' the_current_system, 'survive_possibility, 'certain]]],
[rule10,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
    [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule11,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
    [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule12,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
    [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule13,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_certain],
            ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
    [' the_current_system, 'survive_possibility, 'almost_certain]]],
```

```
[rule14,
        [[con,   ['the_current_system, 'survive_possibility, 'almost_certain],
                 ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
        [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule15,
        [[con,   ['the_current_system, 'survive_possibility, 'quite_possible],
                 ['the_adding_unit_(X), 'survive_possibility, 'certain]],
        [' the_current_system, 'survive_possibility, 'certain]]],
[rule16,
        [[con,   ['the_current_system, 'survive_possibility, 'quite_possible],
                 ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
        [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule17,
        [[con,   ['the_current_system, 'survive_possibility, 'quite_possible],
                 ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
        [' the_current_system, 'survive_possibility, 'more_than(quite_possible)]]],
[rule18,
        [[con,   ['the_current_system, 'survive_possibility, 'quite_possible],
                 ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
        [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule19,
        [[con,   ['the_current_system, 'survive_possibility, 'quite_possible],
                 ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
        [' the_current_system, 'survive_possibility, 'quite_possible]]],
```

```
[rule20,
        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
        [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule21,
        [[con,  ['the_current_system, 'survive_possibility, 'quite_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
        [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule22,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'certain]],
        [' the_current_system, 'survive_possibility, 'certain]],
[rule23
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
        [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule24,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
        [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule25,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
        [' the_current_system, 'survive_possibility, 'more_than(moderate_possible]]],
```

```
[rule26,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
        [' the_current_system, 'survive_possibility, 'moderate_possible]]],
[rule27,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
        [' the_current_system, 'survive_possibility, 'moderate_possible]]],
[rule28,
        [[con,  ['the_current_system, 'survive_possibility, 'moderate_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
        [' the_current_system, 'survive_possibility, 'moderate_possible]]],
[rule29,
        [[con,  ['the_current_system, 'survive_possibility, 'slightly_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'certain]],
        [' the_current_system, 'survive_possibility, 'certain]]],
[rule30,
        [[con,  ['the_current_system, 'survive_possibility, 'slightly_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'almost_certain]],
        [' the_current_system, 'survive_possibility, 'almost_certain]]],
[rule31,
        [[con,  ['the_current_system, 'survive_possibility, 'slightly_possible],
                ['the_adding_unit_(X), 'survive_possibility, 'quite_possible]],
        [' the_current_system, 'survive_possibility, ' quite_possible]]],
```

```
[rule32,
      [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],
               ['the_adding_unit_(X), 'survive_possibility, 'moderate_possible]],
      [' the_current_system, 'survive_possibility, ' moderate_possible]]],
[rule33,
      [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],
               ['the_adding_unit_(X), 'survive_possibility, 'slightly_possible]],
      [' the_current_system, 'survive_possibility, ' more_than(slightly_possible]]],
[rule34,
      [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],
               ['the_adding_unit_(X), 'survive_possibility, 'almost_impossible]],
      [' the_current_system, 'survive_possibility, ' slightly_possible]]],
[rule35,
      [[con,   ['the_current_system, 'survive_possibility, 'slightly_possible],
               ['the_adding_unit_(X), 'survive_possibility, 'impossible]],
      [' the_current_system, 'survive_possibility, ' slightly_possible]]],
[rule36,
      [[con,   ['the_current_system, 'survive_possibility, 'almost_impossible],
               ['the_adding_unit_(X), 'survive_possibility, ' certain]],
      [' the_current_system, 'survive_possibility, 'certain]]],
[rule37,
      [[con,   ['the_current_system, 'survive_possibility, 'almost_impossible],
               ['the_adding_unit_(X), 'survive_possibility, ' almost_certain]],
      [' the_current_system, 'survive_possibility, 'almost_certain]]],
```

```
[rule38,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' quite_possible]],
    [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule39,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' moderate_possible]],
    [' the_current_system, 'survive_possibility, 'moderate_possible]]],
[rule40,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' slightly_possible]],
    [' the_current_system, 'survive_possibility, 'slightly_possible]]],
[rule41,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' almost_impossible]],
    [' the_current_system, 'survive_possibility, 'more_than(almost_impossible)]]],
[rule42,
    [[con,  ['the_current_system, 'survive_possibility, 'almost_impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' impossible]],
    [' the_current_system, 'survive_possibility, 'almost_impossible]]],
[rule43,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' certain]],
    [' the_current_system, 'survive_possibility, 'certain]]],
```

```
[rule44,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' almost_certain]],
    [' the_current_system, 'survive_possibility, 'almost_certain]]]],
[rule45,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' quite_possible]],
    [' the_current_system, 'survive_possibility, 'quite_possible]]],
[rule46,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' moderate_possible]],
    [' the_current_system, 'survive_possibility, 'moderate_possible]]],
[rule47,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' slightly_possible]],
    [' the_current_system, 'survive_possibility, 'slightly_possible]]],
[rule48,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' almost_impossible]],
    [' the_current_system, 'survive_possibility, 'almost_impossible]]],
[rule49,
    [[con,  ['the_current_system, 'survive_possibility, 'impossible],
            ['the_adding_unit_(X), 'survive_possibility, ' impossible]],
    [' the_current_system, 'survive_possibility, 'more_than(impossible)]]]]
```

```
]$

/**** ruleset  for combining system failure frequence possibility  ****/

RB_Combination_Failure:[

/* ruleset for initial system combination */

[initial_combination,

        [rule1,

                [[con,   ['the_current_system, 'failure_frequency, 'any],

                         ['the_adding_unit_(X), 'failure_frequency, 'hourly]],

                ['  the_current_system, 'failure_frequency, ' hourly]]],

        [rule2,

                [[con,   ['the_current_system, 'failure_frequency, 'any],

                         ['the_adding_unit_(X), 'failure_frequency, 'daily]],

                ['  the_current_system, 'failure_frequency, ' daily]]],

        [rule3,

                [[con,   ['the_current_system, 'failure_frequency, 'any],

                         ['the_adding_unit_(X), 'failure_frequency, 'weekly]],

                ['  the_current_system, 'failure_frequency, ' weekly]]],

        [rule4,

                [[con,   ['the_current_system, 'failure_frequency, 'any],

                         ['the_adding_unit_(X), 'failure_frequency, 'monthly]],
```

```
            [' the_current_system, 'failure_frequency, ' monthly]]],

    [rule5,

            [[con,   ['the_current_system, 'failure_frequency, 'any],

                     ['the_adding_unit_(X), 'failure_frequency, 'annually]],

            [' the_current_system, 'failure_frequency, ' annually]]],

/* ruleset for parallel connected units combination */

[parallel_connection,

    [rule1,

            [[con,   ['the_current_system, 'failure_frequency, 'hourly],

                     ['the_adding_unit_(X), 'failure_frequency, 'hourly]],

            [' the_current_system, 'failure_frequency, ' daily]]],

    [rule2,

            [[con,   ['the_current_system, 'failure_frequency, 'hourly],

                     ['the_adding_unit_(X), 'failure_frequency, 'daily]],

            [' the_current_system, 'failure_frequency, ' weekly]]],

    [rule3,

            [[con,   ['the_current_system, 'failure_frequency, 'hourly],

                     ['the_adding_unit_(X), 'failure_frequency, 'weekly]],

            [' the_current_system, 'failure_frequency, ' monthly]]],

    [rule4,

            [[con,   ['the_current_system, 'failure_frequency, 'hourly],

                     ['the_adding_unit_(X), 'failure_frequency, ' monthly]],

            [' the_current_system, 'failure_frequency, ' annually]]],

    [rule5,
```

```
        [[con,   ['the_current_system, 'failure_frequency, 'daily],
                 ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, ' weekly]]],
  [rule6,
        [[con,   ['the_current_system, 'failure_frequency, 'daily],
                 ['the_adding_unit_(X), 'failure_frequency, 'daily]],
        [' the_current_system, 'failure_frequency, ' monthly]]],
  [rule7,
        [[con,   ['the_current_system, 'failure_frequency, 'daily],
                 ['the_adding_unit_(X), 'failure_frequency, 'weekly]],
        [' the_current_system, 'failure_frequency, 'monthly]]],
  [rule8,
        [[con,   ['the_current_system, 'failure_frequency, 'daily],
                 ['the_adding_unit_(X), 'failure_frequency, 'monthly]],
        [' the_current_system, 'failure_frequency, 'annually]]],
  [rule9,
        [[con,   ['the_current_system, 'failure_frequency, 'weely],
                 ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, ' monthly]]],
  [rule10,
        [[con,   ['the_current_system, 'failure_frequency, 'weekly],
                 ['the_adding_unit_(X), 'failure_frequency, 'daily]],
        [' the_current_system, 'failure_frequency, 'annually]]],
  [rule11,
```

```
        [[con,  ['the_current_system, 'failure_frequency, 'monthly],
                ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, ' annually]]]],

/* ruleset for series connected units combination */

[series_connection,

    [rule1,
        [[con,  ['the_current_system, 'failure_frequency, 'hourly],
                ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, ' more_than(hourly)]]],

    [rule2,
        [[con,  ['the_current_system, 'failure_frequency, 'hourly],
                ['the_adding_unit_(X), 'failure_frequency, 'daily]],
        [' the_current_system, 'failure_frequency, ' hourly]]],

    [rule3,
        [[con,  ['the_current_system, 'failure_frequency, 'hourly],
                ['the_adding_unit_(X), 'failure_frequency, 'weekly]],
        [' the_current_system, 'failure_frequency, ' hourly]]],

    [rule4,
        [[con,  ['the_current_system, 'failure_frequency, 'hourly],
                ['the_adding_unit_(X), 'failure_frequency, ' monthly]],
        [' the_current_system, 'failure_frequency, ' hourly]]],

    [rule5,
        [[con,  ['the_current_system, 'failure_frequency, 'hourly],
                ['the_adding_unit_(X), 'failure_frequency, ' annually]],
```

```
        [' the_current_system, 'failure_frequency, ' hourly]]],

   [rule6,

        [[con,   ['the_current_system, 'failure_frequency, 'daily],

                 ['the_adding_unit_(X), 'failure_frequency, 'hourly]],

        [' the_current_system, 'failure_frequency, ' hourly]]],

   [rule7,

        [[con,   ['the_current_system, 'failure_frequency, 'daily],

                 ['the_adding_unit_(X), 'failure_frequency, 'daily]],

        [' the_current_system, 'failure_frequency, ' more_than(daily)]]],

   [rule8,

        [[con,   ['the_current_system, 'failure_frequency, 'daily],

                 ['the_adding_unit_(X), 'failure_frequency, 'weekly]],

        [' the_current_system, 'failure_frequency, 'daily]]],

   [rule9,

        [[con,   ['the_current_system, 'failure_frequency, 'daily],

                 ['the_adding_unit_(X), 'failure_frequency, 'monthly]],

        [' the_current_system, 'failure_frequency, 'daily]]],

   [rule10,

        [[con,   ['the_current_system, 'failure_frequency, 'daily],

                 ['the_adding_unit_(X), 'failure_frequency, 'annually]],

        [' the_current_system, 'failure_frequency, 'daily]]],

   [rule11,

        [[con,   ['the_current_system, 'failure_frequency, 'weekly],

                 ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
```

```
        [' the_current_system, 'failure_frequency, ' hourly]]],
  [rule12,
        [[con,   ['the_current_system, 'failure_frequency, 'weekly],
                 ['the_adding_unit_(X), 'failure_frequency, 'daily]],
        [' the_current_system, 'failure_frequency, 'daily]]],
  [rule13,
        [[con,   ['the_current_system, 'failure_frequency, 'weekly],
                 ['the_adding_unit_(X), 'failure_frequency, 'weekly]],
        [' the_current_system, 'failure_frequency, 'more_than(weekly)]]],
  [rule14,
        [[con,   ['the_current_system, 'failure_frequency, 'weekly],
                 ['the_adding_unit_(X), 'failure_frequency, 'monthly]],
        [' the_current_system, 'failure_frequency, 'weekly]]],
  [rule15,
        [[con,   ['the_current_system, 'failure_frequency, 'weekly],
                 ['the_adding_unit_(X), 'failure_frequency, 'annually]],
        [' the_current_system, 'failure_frequency, 'weekly]]],
  [rule16,
        [[con,   ['the_current_system, 'failure_frequency, 'monthly],
                 ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, ' hourly]]],
  [rule17,
        [[con,   ['the_current_system, 'failure_frequency, 'monthly],
                 ['the_adding_unit_(X), 'failure_frequency, 'daily]],
```

```
        [' the_current_system, 'failure_frequency, 'daily]]],
    [rule18,
        [[con,    ['the_current_system, 'failure_frequency, 'monthly],
                  ['the_adding_unit_(X), 'failure_frequency, 'weekly]],
        [' the_current_system, 'failure_frequency, 'weekly]]],
    [rule19,
        [[con,    ['the_current_system, 'failure_frequency, 'monthly],
                  ['the_adding_unit_(X), 'failure_frequency, 'monthly]],
        [' the_current_system, 'failure_frequency, 'more_than(monthly)]]],
    [rule20,
        [[con,    ['the_current_system, 'failure_frequency, 'monthly],
                  ['the_adding_unit_(X), 'failure_frequency, 'annually]],
        [' the_current_system, 'failure_frequency, 'monthly]]],
    [rule21,
        [[con,    ['the_current_system, 'failure_frequency, 'annually],
                  ['the_adding_unit_(X), 'failure_frequency, 'hourly]],
        [' the_current_system, 'failure_frequency, 'hourly]]],
    [rule22,
        [[con,    ['the_current_system, 'failure_frequency, 'annually],
                  ['the_adding_unit_(X), 'failure_frequency, 'daily]],
        [' the_current_system, 'failure_frequency, 'daily]]],
    [rule23,
        [[con,    ['the_current_system, 'failure_frequency, 'annually],
                  ['the_adding_unit_(X), 'failure_frequency, 'weekly]],
```

```
        [' the_current_system, 'failure_frequency, 'weekly]]],

    [rule24,

        [[con,   ['the_current_system, 'failure_frequency, 'annually],

                 ['the_adding_unit_(X), 'failure_frequency, 'monthly]],

        [' the_current_system, 'failure_frequency, 'monthly]]],

    [rule25,

        [[con,   ['the_current_system, 'failure_frequency, 'annually],

                 ['the_adding_unit_(X), 'failure_frequency, 'annually]],

        [' the_current_system, 'failure_frequency, 'more_than(annually)]]]]

]$
```