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A Fuzzy Approach to Construction Activity Estimation

by

Hyung John Shin, BA., M.Sc.

A Doctoral Thesis submitted in partial fulfilment of the requirements

for the award of Doctor of Philosophy of the

Loughborough University of Technology

June 1994

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ABSTRACT

A Fuzzy Approach to Construction Activity Estimation

Past experience has shown that variations in production rate value for the same work item is attributed to a wide range of factors. The relationships between these factors and the production rates are often very complex. It is impossible to describe an exact mathematical causal relationship between the qualitative factors(QF) and production rates. Various subjective approaches have been attempted to quantify the uncertainties contained in these causal relationships. This thesis presents one such approach by adopting a fuzzy set theory in conjunction with a fuzzy rule based system that could improve the quantification of the qualitative factors in estimating construction activity durations and costs.

A method to generate a Standard Activity Unit Rate(SAUR) is presented. A construction activity can be defined by combining the Design Breakdown Structure, Trade Breakdown Structure and Work Section Breakdown Structure. By establishing the data structure of an activity, it is possible to synthesis the SAUR from published estimating sources in a systematic way. After the SAUR is defined, it is then used as a standard value from which an appropriate Activity Unit Rate(AUR) can be determined.

A proto-type fuzzy rule based system called 'Fuzzy Activity Unit Rate Analyser(FAURA)' was developed to formalise a systematic framework for the QF quantification process in determining the most likely activity duration/cost. The compatibility measurement method proposed by Nafarieh and Keller has been applied as an inference strategy for FAURA. A computer program was developed to implement FAURA using Turbo Prolog.

FAURA was tested and analysed by using a hypothetical bricklayer's activity in conjunction with five major QF as the input variables. The results produced by FAURA

show that it can be applied usefully to overcome many of the problems encountered in the QF quantification process. In addition, the analysis shows that a fuzzy rule base approach provides the means to model and study the variability of AUR.

Although the domain problem of this research was in estimation of activity duration/cost, the principles and system presented in this study are not limited to this specific area, and can be applied to a wide range of other disciplines involving uncertainty quantification problems. Further, this research highlights how the existing subjective methods in activity duration/cost estimation can be enhanced by utilising fuzzy set theory and fuzzy logic.

ACKNOWLEDGEMENTS

It is quite difficult to express in a few line my gratitude towards all the people that have helped me during the course of my doctoral study in UK.

I am deeply grateful to my father who has financed and encouraged me for more than thirty years since I started my education. I am sure that he is happier than myself for this moment.

To my wife and son who have waited so long and patiently for this work, I have to express my special thanks.

I want to thank my research director, Professor R. McCaffer, for guidance and encouragement.

I want to thank my supervisor, Professor, V. Torrance, at University College London, for all the support and direction he provides me during my stay in Edinburgh and Loughborough.

I want to express a special thank to my supervisor, Dr. Tony Thorpe, for the guidance, insightful suggestions and friendship he provides me during my stay in Loughborough.

I owe much to my colleagues, Dr. You-guang Pan, Mr. Chris Carter who has sorted out my English problems. I want to thank to my friends, Korean students, Hai-shan Huang, Alex Fortune who all have encouraged and assisted me during my stay in this country.

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1.1 Research Motivation

The basic purpose of project management is the planning and control of actual expenditure for an end product, and to derive signals for management action from the comparison to the original estimate through progress report as shown in Fig.1.1.

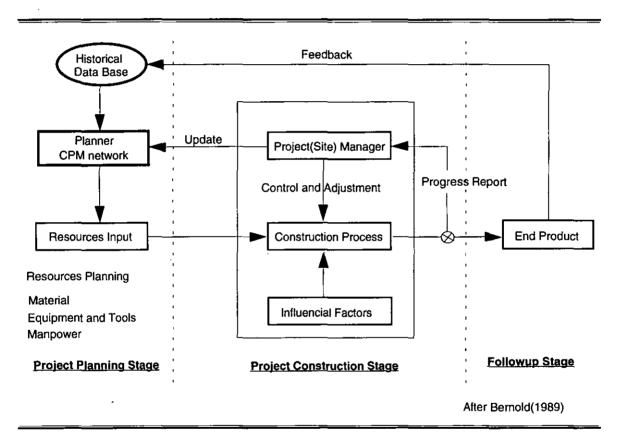


Fig. 1.1 Project Management System

Construction managers(planners) have used the CPM/PERT network methods for many years as a project management tool. These two approaches are commonly utilised to represent a project in a form of a network diagram and to perform the necessary calculations on the diagram to determine a project duration/cost. The planning stage estimate provides the basis of a standard for the purpose of control. Measuring progress in

the project control stages requires a predetermined standard which provides a benchmark for the evaluation of progress. Moreover, this plays a very crucial role in the construction management functions such as communication flows, set-up targets, and claim and dispute settlements etc.. If the original activity duration/cost estimates are not accurate, then a planning system can not work. Adams(1981) states the importance of activity duration estimation as follows:

"Time estimates for the individual project activities are critical to use of network planning tools such as CPM or PERT. They form the basis of all analytical operations carried out on the network, and the regulating work schedule can be no more accurate than the basic estimates from which it is calculated. It is therefore highly advantageous to obtain the most accurate activity estimates feasible."

However, activity duration estimation has received little systematic attention in practise (Smith 85, Hendrickson 87). This may be due to the fact that a more detailed analysis for the activity duration is considered to be uneconomical as the estimated activity durations obtained by using average productivity rates, that reflect general and nation-wide averages, appears to reasonably match the actual duration. For this reason, it is common practice for project planners to use average productivity rates obtained from available estimating sources or the company's own records when they estimate activity durations.

This approach, however, ignores the uncertainty associated with the data which is used to estimate activity duration/cost. Furthermore, each construction process on site is subject to a wide range of factors which can significantly influence the crew performance. Thus, in most cases of activity duration estimate, a standard(average) production unit rate has to be adjusted to take account of the variety of variables faced in a particular project. This process relies on considerable expertise and is not a precise scientific exercise, but an art

which involves intuition, knowledge and experience(Flanagan 1982,1987, Levitt 1985, Gray 1986, Hendrickson 1987). Hence, there is a need to investigate a systematic approach which can capture and utilise the expertise of construction planners for estimating activity duration to formulate this largely subjective process. This thesis investigates better methods of using heuristic knowledge to enhance the accuracy of activity estimation. Whilst absolute accuracy is impossible to achieve, the opportunity exists to enhance current approaches to determine activity durations. This overall goal provides the motivation for this study.

1.2 Previous Studies in Modelling Activity Duration

In previous studies, approaches to the heuristic activity duration modelling problem, can be classified into three domains, which are: the subjective factor correction method; knowledge based systems; and fuzzy systems approach.

A. Subjective Factor Correction Approaches

The prevailing subjective approach to determine activity duration is by applying +/- x % to the initial estimate as a contingency allowance for the uncertainty(Jaffari 1984, Hendrickson et al. 1987, Carr et al. 1991). The determination of contingency allowance coefficient relies upon the assessor's subjective judgement based on intuition, knowledge or experience. However, simply applying +/- x % of the initial estimate to compensate for the contingency factors cannot solve the fundamental problem in factor quantification. In this approach, history repeats itself and the result becomes arbitrary because it gives no information about the cause and consequence relationships(Traylor et al. 1984). It may be

sufficient for performing the task, but it lacks a formalised method which can explain clearly the casual relationships.

B. Knowledge Based Systems(KBS) Approach

The limitation of the subjective factor correction method can be enhanced by applying a KBS approach, since this provides a formalised method of utilising heuristic knowledge in problem solving. It provides a framework for utilising expert knowledge by providing facilities such as knowledge elicitation procedures, knowledge representation schema, knowledge based inference mechanisms and input/output interfaces. Examples of KBS aimed at modelling activity duration are Time(Gray 1986,1987), Mason(Hendrickson 1987), and Ratu-AJ(Kähkonen 1989). Herbsman(1990b) and Duff(1990b) have also proposed proto-type conceptual activity duration models.

C. Fuzzy Systems Approach

In reality, many phenomena are ill-structured and complex and it is difficult to use precise statements to describe and characterise them. Rather, vague assertions to describe uncertainty situations are more compatible with the range of observed facts. These vague concepts can be modelled by using the fuzzy set theory developed by Zadeh(Zadeh 1965). The fuzzy set theory is a method of quantifying uncertainty via a set of formal mathematically based rules. In particular, it allows the quantification of linguistic terms which characterise vague situations(or uncertainty) into numerical values. The basis of fuzzy set theory is described more fully in chapter 2.

Prior to this study, Ayyub and Haldar(1984) first examined the applicability of fuzzy set theory in activity duration estimation. They tried to quantify the impact of factors on activity duration by using a simple example. Kangari(1987) re-examined the Ayyub and

Haldar study in his construction risk analysis project report. He used the same frame work suggested by the Ayyub and Haldar study. He performed a sensitivity analysis to examine the effect on an activity duration by changing membership values in fuzzy sets. He found that the changing membership values in fuzzy sets has little impact on an activity duration, however, the changing range in fuzzy sets has a large impact on an activity duration.

These two studies are based on the previous fuzzy applications in structural damage assessment domains(Blockley 1975, Brown 1979, Yao 1980, Brown and Yao 1983). Ross(1990) and Yeh(1991) have further extended the fuzzy set theory application in this domain. Wu and Hadipriono(1994) have presented a simplied fuzzy approach to estimate the duration of activity. They employ an angular fuzzy set model which uses a single number to represent a linguistic term. They proposed a model, Activity Duration Decision Supporting System(ADDSS), that can be used to quantify the impact of various factors on activity duration in conjunction with the fuzzy modus ponens deduction techniques.

1.3 Problem Statement

The key problem in estimating an activity duration/cost is how to determine the Activity Unit Rate(AUR) under a given set of factors, since the AUR is a function of many factors. An activity duration/cost calculation is very simple matter if the data used in this process is accurate. In such circumstance, it does not require complex mathematics and theories rather it needs a good data base management system. However, in reality, a construction process on site is subject to a wide range of factors which can influence the crew performance. Thus the AUR will vary depending on which of the factors are present and

to what degree. This variability of AUR caused by the factors is referred to as the susceptibility. The susceptibility measurement function can be expressed by the following hypothetical function:

$$Y = f(V1,...,Vn)$$
(1-1)

where Y = susceptibility; and Vi = independent variable i(i=1,...,n).

The principle problem examined in this study is how to determine this function. There are a variety of approaches to model this function. In modelling such a susceptibility function, some of the consideration for a realistic model are: limitation of data in relation to the casual relationship; the need for human knowledge and experiences; formulation of the rule base; and the inference mechanism that can be used in the modelling process. These issues are discussed later in the thesis. In this study, a heuristic method in conjunction with a fuzzy rule based system was developed to model this function.

The secondary problem is the selection of a set of independent variables as significant factors. In this study, only the the qualitative factors are considered such as design aspects, management control, crew related factors, site conditions, and weather. These factors were chosen for demonstration purposes and to test and analyse the system developed in this study. This study is therefore limited in the scope but the fuzzy system developed are applicable to similar factors which can be added or deleted as necessary.

1.4 Objectives

The objectives of this study are:

- To investigate and propose a formalised method of utilising heuristic knowledge for the determination of activity duration/cost allowing for uncertainty for project planning and control purposes; and
- To examine the application of fuzzy set theory and fuzzy logic to implement the formalised method.

To achieve these objectives the following four steps are required.

- Propose a method to generate a Standard Activity Unit Rate(SAUR).
- Develop a method for an adjustment mechanism.
- Develop a computer program to implement the adjustment mechanism.
- Evaluate the adjustment mechanism.

1.5 Justification for a Fuzzy Approach

A. Reasons for using Fuzzy Set Theory

To date, considerable effort to quantify influential factors impact on production unit rate have been made to the quantitative(objective) approach(Oxley 1975, Adrian 1976, Duff 1979, 1990, Harris 1985,1989, Thomas 1987,1990,1994, Sanders 1989, Herbsman 1990, Horner 1981,1987,1990, Olomolaiye 1990). The prevailing theories used in the productivity models are based on statistical and probability theories in conjunction with work study techniques. For the quantitative factors, these theories are workable. However, the conventional quantitative approach is very difficult to apply in quantifying the impact of the qualitative factors such as management control, crew related factors, weather effect, etc. for the determination of Activity Unit Rate(AUR). This is either due to the difficulty in collecting sufficient data to yield a statistical model for the causal relationship, or even the impossibility of collecting data in some cases with respect to: (1) the factor measurement problem; and (2) the susceptibility measurement problem. Zadeh(1973) states the problems of the conventional quantitative approach to modelling uncertainty as:

"The traditional techniques of uncertainty system analysis are not well suited for dealing with humanistic systems because they fail to come grips with the reality of the fuzziness of human thinking and behaviour. Thus, to deal with such systems realistically, we need approaches which do not make a fetish of precision, rigor, and mathematical formalism, and which employ instead a methodological framework which are tolerant of imprecision and partial truths."

With this perspective, it may be possible to use fuzzy sets to describe uncertainties contained in the causal relation. To explain this, consider a statement like ' if the site

conditions are *bad*, then AUR is *high* (i.e., will take about 4.5 MH/M²). In this sense, an estimated AUR under a certain condition is a fuzzy notion of unit rate. It is not necessary to have a statistical or probability notion to estimate the AUR, since the AUR is neither completely an experimentally controlled repeated condition nor a random occurance. In such circumstances, measuring site conditions and susceptibility in AUR are subjective measurement, i.e., fuzzy estimates, due to absence of standards or methods to measure them. Fuzzy set theory developed by Zadeh(1965) is able to deal with such vagueness arising from subjectivity which is inherent in the human thought process. Kaufmann and Gupta(1988) state the role of fuzzy set theory as:

"Fuzzy set theory is body of concepts and techniques that give a form of mathematical precision to human cognitive processes that in many ways are imprecise and ambiguous by standards of classical mathematics. An underlying philosophy of the theory of fuzzy sets is to provide a strict mathematical framework, where imprecise conceptual phenomena in modelling and decision making may be precisely and rigorously studied. It provides for a gradual transition from the realm of rigorous, quantitative and precise phenomena to that of vague, qualitative and imprecise conceptions. This theory enables one to characterise imprecision in terms of 'fuzziness', a concept to which one can assign many meanings."

This observation opens the possibility of using the concept of fuzziness in solving AUR determination problem.

B. Reasons for Using Fuzzy Logic

Kähkonen(1989) summarised the usefulness of Knowledge Based Systems(KBS) for determining activity duration as:

 KBS enable systematic and detailed problem solving methods to be applied quicker than is possible manually.

- KBS can assist in determining site activity duration
- Expertise needed to cope with complex tasks can be captured and preserved within a knowledge base.
- Expertise, once acquired, can be analysed and formalised in a way that lends itself to
 heuristic forms of problem-solving; in order words, KBS development can be used as a
 research and development tool.

For these reasons, investigating KBS for determining activity duration appears quite promising. However, much of human heuristic knowledge used in the knowledge based system is vague in its nature, especially where there is a lack of information/data. This heuristic knowledge is neither totally true or false, i.e., there is inherently some degree of vagueness(fuzziness). In these circumstances, it would be better to allow to use linguistic terms, which is fuzzy information to estimate vague situations, rather than to use numerical values. However, the rules used in the conventional knowledge based systems require the precise numerical values. For example, a typical rule format used in the most expert systems in activity duration(or productivity analysis) is 'If factor i is A, then adjust +/- B % of standard productivity.' In this case, the values, A and B, in a rule are the precise numerical values. This approach has difficulties in justifying the accuracy of the values, A and B, used in a rule, particularly, when dealing with uncertainty situations or data deficient situations. Fuzzy sets theory can overcome this shortcoming by allowing for the use of linguistic terms to represent the vagueness(uncertainty) contained in the knowledge provided by experts.

Hence, if we can capture expert's knowledge into a fuzzy rule format which uses ligustic terms, it can provide a clue to the reasoning process which will convert a given input value into an approximate solution via the fuzzy logic. This is the reason for employing the fuzzy logic approach which is based on the approximate reasoning theory(Zadeh 1975b, 1975c, 1978, 1983, Mizumoto at al. 1979, Mizumoto at al. 1982) to deal with vague or imprecise information in determing activity duration/cost in this study.

1.6 Definitions

The following definitions are used in this study.

Activity: An activity can be defined as a time and resource consuming event for the installation of a building component for a specified work section used by planners for time and cost control purposes.

Activity Unit Rate(AUR): The AUR is defined as the number of Man Hours(MH) needed to undertake a unit work of an activity. This can be defined by:

AUR = Total Paid Time for Activity / Quantity of Activity(1.2)

In this way, the AUR can only be defined after an activity is completed. However, this definition does not provide detailed information about the nature of activity. Thus EQ 1.2 can be described in more detail as:

$$AUR = \frac{\sum_{i=1}^{n} T_i}{AO} \tag{1.3}$$

where T_i is duration of task i(i=1,2,...,n) and AQ is Quantity of activity j. T_i can be calculated by:

$$T_i = \frac{TQ_i}{P_i \times N} \tag{1.4}$$

where TQ_i is Quantity of Task i,

 P_i is a crew task unit rate i,

N is a number of crew assigned to the task i.

Qualitative Factors: The qualitative factors are those which can not be measured objectively thier consequences on production unit rates. The factors included in this category are crew motivation, management control efficiency, complexity of design aspect, weather condition, site condition, etc.. These factors can used to represent the uniqueness of a project, since each project differs from past projects.

Causal Relationship: The term, causal relationship, refers to the causes and consequences relation. A cause is, in general, defined as a mechnism influencing the object. In this study, causes refer to the qualitative factors only. The object could be a project level, WP level, activity level or task level, i.e., dependent upon the level of detail of analysis. In this study, the activity level is used as the objective. A consequence is a result of the influence by the factors on the object. In this study, the AUR is used as a measure of the consequence.

1.7 Achivements

The research objectives described in section 1.4 have been achived and are described in chapter 5. The analysis(chapter 6) shows that the fuzzy system developed in this study can be applied usefully to quantify factors affecting activity duration/cost when preparing a project schedule(program). Although the domain problem was in estimating activity duration/cost, the principles and system presented in this study are not limited to this specific area. In fact, they can be applied to a wide range of other discipline involving uncertainty interpretation problems.

The envisaged benifits from the fuzzy system developed in this study are:

- It can assist planners to produce a more reliable activity duration/cost estimation.
- It provides an insight into how the impact of the qualitative factors(QF) on an activity duration can be quantified.
- It provides a systematic and formalised framework for utilising hueristic knowledge for problem solving in determing activity duration/cost.
- Its generic nature allows the modelling and study of the variablity in AUR for various types of activities.

1.8 Thesis Organisation

This thesis consists of seven chapters. Brief descriptions of each chapter are given below:

Chapter 2: This chapter reviews two aspects which are; (1) the elements of fuzzy set theory, and (2) the previous studies in activity duration. In the first part, fuzzy set theory is reviewed briefly to help in understanding the fuzzy rule based system in chapter 5. In the second part of this chapter, the activity duration models previously developed are described.

Chapter 3: This chapter discusses the research concept. Firstly, the activity production system is examined. From this, the casual relationship used in this study is defined. Finally, the research concept is presented in this chapter by examining the problems associated with the causal relationship.

Chapter 4: This chapter describes the method of generating standard AUR. The method of generating the construction activity is presented by combining the design breakdown structure, the trade breakdown structure and the work section breakdown structure. Then by establishing a work classification structure, it is possible to generate the standard AUR. An example is provided to demonstrate these procedures.

Chapter 5: This chapter presents a proto-type fuzzy rule based system called 'Fuzzy Activity Unit Rate Analyser(FAURA)'. The input/output, rule base and inference mechanism are described. A computational step to implement the FAURA is also described.

Chapter 6: This chapter analyses the FAURA by using bricklayer's activity with five factors. First, the procedures needed to build a fuzzy rule based system are examined and an example rule base is designed for the analysis. The verification analysis with discussion is provided. Finally sensitivity analysis is undertaken to examine the capability of the FAURA.

Chapter 7: The research conclusions are summarised and further research recommendations are suggested in this chapter.

Fig. 1.2 shows the structure of the thesis.

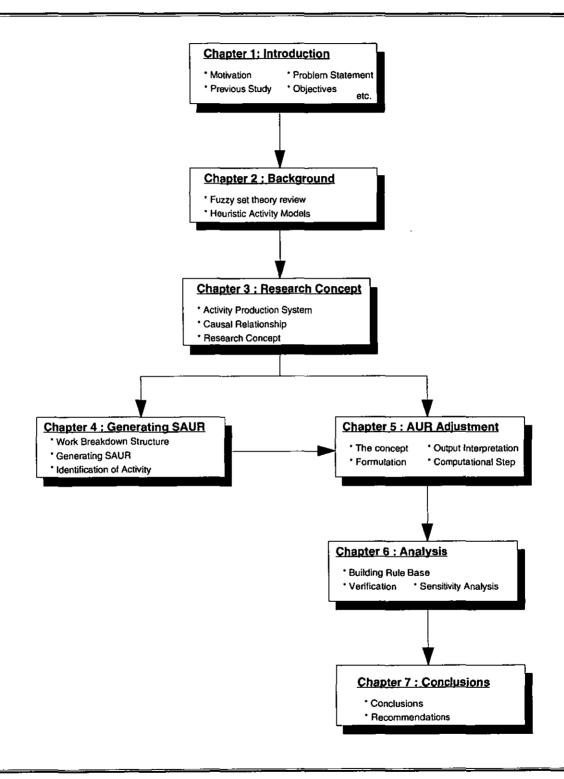


Fig. 1.2 Structure of Thesis

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CHAPTER 2 BACKGROUND

2.1 Introduction

This chapter reviews the elements of fuzzy set theory which provides the basis for developing the fuzzy rule based system described in chapter 5. Previous studies of activity duration models are also reviewed to provide the framework for the main study.

2.2 Introduction of Fuzzy Set Theory

We often use linguistic terms(variables) to describe a vague situation. These linguistic terms contain uncertainty in their meaning. In order to incorporate these uncertainties into an analysis, they need to be interpreted into mathematical measures. Zadeh(1965) laid the foundations of fuzzy set theory to quantify linguistic terms into numerical terms. For example, consider a statement such as 'AUR is *high* if the design aspect is bad'. This implies that 'AUR is *high*(or it will take about 4.5 MH/M²)' is a convenient nearest answer to express the approximate AUR, and it is a subjective measurement of AUR which is a fuzzy notion of the estimate. The vagueness contained in the linguistic term can be interpreted by a fuzzy set. A fuzzy set is defined by a membership function. The following sections describe the basic fuzzy set theory.

2.2.1 Notation of Fuzzy Sets

A. Fuzzy Membership Function

For a non-fuzzy set or a crisp set A, then the membership function is expressed as:

$$f_A(x) = {1, \text{ if and only if } x \in A \atop 0, \text{ if and only if } x \notin A}$$
(2.1)

where $f_A(x)$ indicates that an element x belong to set A.

This implies that its membership value can only take two values 0 and 1 depending on whether x does or does not belong to A. In fuzzy set theory, the membership values may take any values in the range 0 to 1. To explain the notation of fuzzy sets, let $U=\{u\}$ denote the collection of elements in the universe of discourses, U. A fuzzy set A in U is characterised by a membership function $\mu_A(u)$ which is defined as real number in the interval [0,1], with the value of u representing the "grade of membership" of u in A. Symbolically, a fuzzy set A is expressed depending on the type of elements in the set, as a discrete membership function or a continuous membership function. A discrete membership function is expressed by a set of ordered pairs as:

$$\mu_{A}(u) = \mu_{1} / u_{1} + \mu_{2} / u_{2} + \dots + \mu_{n} / u_{n}$$

$$= \sum_{i=1}^{n} \mu_{i} / u_{i}$$
(2.2)

where u_i is the value of the element,

 μ_i is the membership grade for the value of u_i ,

'I' sign is the separator,

'+' sign denotes the union,

 Σ' sign denotes the union.

or in the continuous form as:

$$A = \int_{u=U} \mu_A(u) / u$$
(2.3)

where the integral sign denotes only continuous summation.

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For example, consider u to be the element of unit rate of activity j(AURj) which may range from extremely high AUR, i.e. u=8 MH(Man Hours)/M², to extremely low AUR, i.e. u=2 MH/M². By dividing the range of AUR into increment of 0.5 MH, 'low AUR', as a linguistic value can be interpreted as:

Low AUR =
$$(1/2, 0.9/2.5, 0.7/3, 0.5/3.5, 0.1/4)$$
(2.4)

where the value of u are 2, 2.5, 3, 3.5, and 4, and the corresponding membership values are 1, 0.9, 0.7, 0.5 and 0.1, respectively. Other values (4.5-8) of u have 0 membership values to the subset 'low AUR'. The assignment of membership values to the corresponding elements (or members) is based on the assessors subjective judgement, since there is no exact generalised membership function which defines the membership values of a fuzzy set. Similarly, Average AUR, and High AUR could be interpreted as follows:

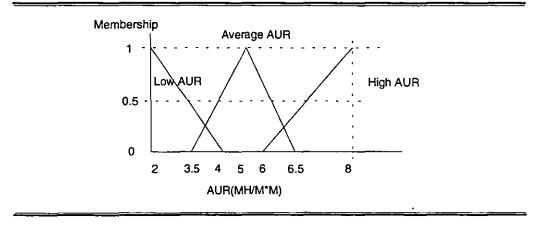


Fig. 2.1 Example Fuzzy Sets

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Each line in Fig.2.1 is representing the fuzzy set Low, Average and High. The X axis represents AUR domain - the real line AUR(MH/M²), and the Y axis represents the membership values - the unit interval [0,1].

As mentioned above, the assignment of membership value has to rely on the assessors subjective judgement. There have been several studies to define standard membership functions(Chameau 1987, Turksen 1991). However, there is no guarantee that the standard functions will produce accurate membership values(Zadeh 1975a). The reason for using the standard membership functions, in most cases of fuzzy applications, is for the convenience of generating membership values and for simplifying the series of calculations involved in the analysis. It is not intended to discuss the various standard membership functions here. These functions are described in more detail in Kaufmann and Gupta(1988).

2.2.2 Fuzzy Operations

Some basic but useful operations are reviewed in this section.

The union, intersection and complementation operation of fuzzy set A and B are defined as:

Union:
$$\mu_{A \cup B}(u) = \max \{ \mu_A(u), \mu_B(u) \}$$
 (2.7)

Intersection:
$$\mu_{A \cap B}(u) = \min\{\mu_A(u), \mu_B(u)\}$$
(2.8)

Complementation:
$$\mu_{\overline{A}}(u) = 1 - \mu_{A}(u)$$
(2.9)

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The union, intersection and complementation operation are summarised by using the following example.

Example:

For the demonstration purpose, let fuzzy sets, A and B be described as:

$$A = 0/1, 0.3/2, 0.5/3, 1/4,$$
 (2.10)
 $B = 1/1, 0.7/2, 0.4/3, 0/4.$ (2.11)

Then by using EQ.2.7 to EQ.2.9, the union, intersection and complementation operation can be calculates respectively as:

Union: $A \cup B = (1/1, 0.7/2, 0.5/3, 1/4),$

Intersection: $A \cap B = (0/1, 0.3/2, 0.4/3, 0/4)$,

Complementation: $\overline{\mathbf{A}} = (1/1, 0.7/2, 0.5/3, 0/4)$.

2.2.3 Fuzzy Relation

A fuzzy proposition describes a certain relationship between two fuzzy sets A and B. This relation is referred to a fuzzy relation, R. Then, the fuzzy relation, R, from A to B is a fuzzy subset of the Cartesian product $U \times V$, where $A \in U$ and $B \in V$. The conditional statement such as 'if X is A then Y is B' is represented by the R and defined as follows:

$$R = \mu_{R}(u, v) = \min(\mu_{A}(u), \mu_{B}(v)); u \in U, v \in V \quad \dots (2.12)$$

The relation, R, is usually expressed in matrix form as:

where $\mu_R(u_i, v_i)$ indicate the joint membership value for the ordered pair (u_i, v_i) , and is a measure of association between u_i and v_i . It is computed as taking the minimum membership value of $\mu_A(u_i)$ and $\mu_B(v_i)$. For example, consider a fuzzy conditional statement such as 'If the design aspect is $complex(Fuzzy\ set\ A)$ then AUR is $high(Fuzzy\ set\ B)$ '. Defining fuzzy set B, high, by EQ.2.6 and fuzzy set A, complex, as:

Complex design =
$$(0.1/0.7, 0.5/0/8, 0.7/0.9, 1/1)$$
.....(2.14)

Then the fuzzy relation, R, by using EQ.2.12 and EQ.2.13 becomes

Note that the membership values of the second row in EQ.2.15 are defined as follows:

$$\mu_R(0.8, 6) = \min(0.5, 0.1) = 0.1$$

 $\mu_R(0.8, 6.5) = \min(0.5, 0.5) = 0.5$

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$$\mu_R(0.8,7) = \min(0.5,0.7) = 0.5$$

$$\mu_R(0.8,7.5) = \min(0.5,0.9) = 0.5$$

$$\mu_R(0.8,8) = \min(0.5,1) = 0.5$$

The fuzzy relation is used to construct a fuzzy rule in a matrix form. From this with a given input fuzzy set, it is possible to deduce a conclusion. This process is described in the next section.

2.2.4. Fuzzy Compositional Rule of Inference

The compositional rule of inference(Zadeh 1975c) states that if R is a fuzzy relation from to V, and A* is a fuzzy subset of U, then the fuzzy subset of B* of V which is induced by A* is denoted by:

$$B^* = A^* \circ R$$
(2.16)

where o is max-min operator.

The B* is obtained by using the max-min compositional rule of inference as follows:

$$\mu_{g*}(v) = \max_{u} \{ \min_{v} \{ \mu_{A*}(u), \ \mu_{R}(u,v) \} \} \quad(2.17)$$

EQ.2.17 yields the membership values for a fuzzy set B* induced by the fuzzy set A* and fuzzy relation, R.

To illustrate the computational process, EQ.2.15 is used for a fuzzy relation between complex design and high AUR. Suppose a new fuzzy subset, say very complex design(A*) has been proposed, and is given by:

$$A^* = A^2 = (0.01/0.7, 0.25/0.8, 0.49/0.9, 1/1).$$
 (2.18)

Then from EQ.2.16,

$$B^* = A^* \circ R = (0.01, 0.25, 0.49, 1) \circ \begin{bmatrix} 6 & 6.5 & 7 & 7.5 & 8 \\ \hline 0.7 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.8 & 0.1 & 0.5 & 0.5 & 0.5 & 0.5(2.19) \\ 0.9 & 0.1 & 0.5 & 0.7 & 0.7 & 0.7 \\ 1 & 0.1 & 0.5 & 0.7 & 0.9 & 1 \end{bmatrix}$$

Then, the results of a new 'high AUR', B*, is defined by the composition operator by using EQ.2.17 as:

$$B^* = (0.1/6, 0.5/6.5, 0.7/7, 0.9/7.5, 1/8)...(2.20)$$

The first membership value, 0.1, in EQ.2.20 is obtained by taking the maximum value of $\{\min(0.01,0.1), \min(0.25,0.1), \min(0.49,0.1), \min(1,0.1)\} = \max(0.1, 0.1, 0.1, 0.1) = 0.1$. The rest of the membership values in EQ.2.20 are obtained by repeating the same process mentioned above by taking the next column in the matrix in EQ.19.

Further details regarding to the fuzzy compositional rule of inference are contained in Zadeh(1975b,1975c), Dubois and Prade(1991) and Nafarieh(1991).

2.3 Heuristic Approaches in Activity Duration

There have been various heuristic studies aiming at improving the accuracy of activity duration estimation. Garza-Rodriguez(1988) defined the heuristic approach as:

"an approach using knowledge which evolves from experience of repeatedly solving the same or similar types of problems rather than from some elegant theoretical foundation."

In this approach, domain-specific knowledge is the key to the problem solving function.

In this section, the various approaches for the estimation of activity duration are examined with particular reference to heuristic modelling since this forms the subject of this study. The various studies in relation to this subject are organised into three sections: 1) fuzzy systems; 2) subjective factor correction methods; and 3) expert system approaches.

2.3.1 Fuzzy Activity Duration

Ayyub and Haldar(1984) examined the applicability of the concept of fuzzy sets in determining activity duration. Weather conditions and labour skill were used as example factors to illustrate the fuzzy computational process. Fig. 2.2 shows this process.

In order to determine activity duration, it is necessary to define the R relation and the S relation. From the R and S relationships, the T relation which is the relation between frequency of occurrence(FO) and activity duration(D) can be determined through the fuzzy composition.

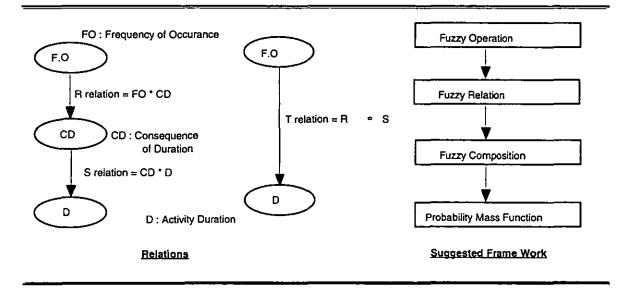


Fig. 2.2. Fuzzy Activity Duration

After the T relationship is determined, then it is possible to determine an activity duration by using the probability mass function. The fuzzy relations and composition for each factor are constructed by using the following equations.

A) R relation: a relation between Frequency of Occurrence(FO, x) and Consequences on Duration(CD, y)

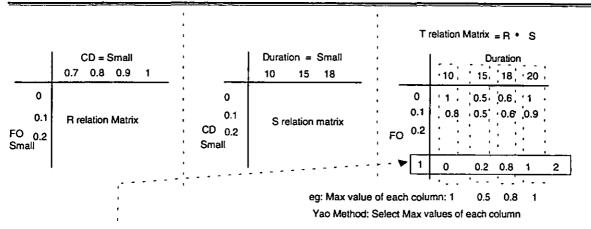
$$\mu_R(x, y) = \mu_A(x) \wedge \mu_B(y)$$
(2.21)

B) S relation: a relation between CD and Activity Duration(D, z)

$$\mu_s(y, z) = \mu_B(y) \wedge \mu_C(z)$$
(2.22)

C) T relation(Composition): a relation between FO(x) and Duration(z) $\mu_{R \circ S}(x, z) = \max_{y} [\min \{ \mu_{R}(x, y) , \mu_{S}(y, z) \}] \dots (2.23)$

The detailed computation is shown in Fig.2.3.



Ayyub and Haldar suggestion: Select a row which maximizes the product of row summation and the corresponding frequency.

Example : Weather condition and consequences on activity duration

1. Frequence of occurrence(FO) is small 2. Consequences on duration(CD) is small 3. Duration is small

Fig. 2.3 Example of Fuzzy Calculation

After the row which maximises the product of raw summation and the corresponding frequency is defined, it is possible to define the activity duration by using the probability mass function. They concluded fuzzy set theory provides a more practical and efficient mechanism than the conventional theories such as statistics or probability to handle uncertainty situations. More details can found in Ayyub and Hardar(1984).

Kangary(1987) re-examined the Ayyub and Haldar study. He undertook a sensitivity analysis to examine the fuzzy system proposed by Ayyub and Haldar. He examined the impact on activity duration in two aspects: 1) changing membership values in the fuzzy set; and 2) changing the range in the fuzzy set. He concluded that changing membership values in a fuzzy set has a little impact on activity duration. However, changing the range in a fuzzy set has a large impact on an activity duration.

Very recently, Wu and Hadipriono(1994) developed a model, Activity Duration Decision Supporting System(ADDSS), that can be used to quantify factors impact on activity duration. The system employs fuzzy modus ponens deduction techniques in conjunction with the angular fuzzy set model which uses single numbers to represent linguistic terms. This system has quite similar features to the fuzzy rule based system called 'Fuzzy Activity Unit Rate Analyser(FAURA)' developed in this study. The similarities are: 1) using fuzzy modus ponens technique for an inference mechanism; 2) using fuzzy sets to represent linguistic terms; and 3) using activity duration as system objective. However, there are several distinctive differences between them. These are shown in Table 2.1.

	ADDSS	FAURA	
1) Fuzzy Set	Angular Fuzzy Set	Zadeh's Standard Membership Function	
2) Inference	Compositional Rule	Compatibility Measurement	
	(Implication Approach)		
3) Rule Base	None	Yes	
4) Object Function	Activity duration	Activity Unit Rate	

Table 2.1 Comparison Between ADDSS and FAURA

2.3.2 Subjective Factor Correction Methods

There have been several studies on the subjective factor correction methods. These methods are not based on the formal theory of statistics or probability, relying on the researcher's subjective opinion. This section describes these methods briefly.

A. Jaffari's approach

Jaffari(1984) introduced the job-management efficiency factor, f, to take account of uncertainties in activity duration estimation. He introduced the following equation:

$$D = \frac{Q}{f} \times q \tag{2.24}$$

where, D is the duration of the activity j,

Q is the total quantity of work in the activity j,

f is the job-management efficient factor,

q is the ideal productivity of the crew.

The expected productivity(Ep) is represented by:

$$Ep = q \times f \qquad (2.25)$$

This implies that if f value is close to unity, 1, and hence the job management efficiency is close to the ideal condition, the duration will be close to the ideal duration. The f value represents the overall measure of factors' impact on the ideal crew productivity. Jaffari suggested that the value of f is typically between 0.4 and 0.8, and concluded that actual productivity tends to be close to that Expected productivity(Ep) when no major external disturbance is observed. The determination of f relies purely on the observers subjective opinion.

B. Productivity Multiplier(PM) concept

One way of adjusting duration to allow for factors that affect productivity is to use multipliers on duration's which have been calculated under an ideal set of working conditions. An adjustment of initial activity duration can be obtained from the following equations.

$$D = \frac{TMH}{8.5 \times N} \tag{2.26}$$

where D is duration of activity,

TMH is total required Man Hours to complete the specified activity j,

8.5 is working hours per day,

N is number of a crew.

The TMH is then calculated by:

$$TMH = Q \times PM$$
(2.27)

where Q is quantity of activity j,

PM is the productivity multiplier.

A PM is obtained from the following equation.

$$PM = P \div \frac{1}{1 + \sum_{i=1}^{n} F_i}$$
 (2.28)

where, P is the ideal productivity rate(or unit rate) in MH/Unit,

Fi is the value of Factor i(i = 1, 2, ..., n),

$$\frac{1}{1 + \sum_{i=1}^{n} F_i}$$
 is an multiplier.

Substituting EQ.2.28 into EQ.2.27 becomes:

$$D = Q \times P \div \frac{1}{1 + \sum_{i=1}^{n} F_i} \qquad (2.29)$$

Example

Ideal Productivity of a crew (P) is 4.5 MH/M²,

Quantity of an activity(Q) is 100M².

N=3.

Each factor affecting duration is established as shown in the table below.

Fi	Adjustment Factor Value				
F1: Design Factor	0.1	0.2	0.3		0.5
F2: Management Factor	0.1	0.2	0.3	******	0.5
	0.1	0.2	0.3		0.5
Fn	0.1	0.2	0.3		0.5
ΣFi <u>.</u>			<u>.</u>		

Table 2.2 Table based Factor Ranking

The small adjustment value shows that factor i is favourable, and when the adjustment factor value reaches its maximum, factor i is the worst case. For example, a design factor can be expressed as:

Conditions Adjustment Value

1. Simple design feature 0.1 (Min)

2. Fairly standard design feature 0.3 (Normal)

3. Complex design feature

0.5 (Max)

Similarly, the management factor ranking table can be established. To illustrate this, consider two factors, complex design and good management, then the PM would be:

PM =
$$4.5 / (1 / (1 + (0.5 + 0.2))) = 7.65$$
 MH/ M²
Thus, D = $(100 \times 7.65) / (8.5 \times 3) = 30$ days

In this approach, the first step is to define the ideal productivity rate under the ideal working conditions. The productivity is then reduced, with respect to the conditions represented by the factors, by using the multiplier(EQ2.28). The productivity multiplier is a more reliable approach than Jaffaris's method, as more consideration is given to the influencing factors.

C. Lichtenberg Modified PERT Approach

In 1957, a technique called the Program Evaluation and Review Technique(PERT) was developed to take account uncertainties in determining a project duration(Ahuja 1976). PERT requires three subjective time estimates for pessimistic, optimistic and most likely durations to estimate the mean and variance of the duration's distribution, which is assumed to be a beta distribution. This techniques leads to difficulties in determining the three time estimates and the degree of skew in the distribution curve. The determination of these estimates relies on the intuition and knowledge of the planners. Lichtenberg(1976) shows that, in practise, the duration is tend to be skewed towards the pessimistic duration, as shown on the right of Fig. 2.4. Therefore, he proposed a modified version of the PERT as shown below:

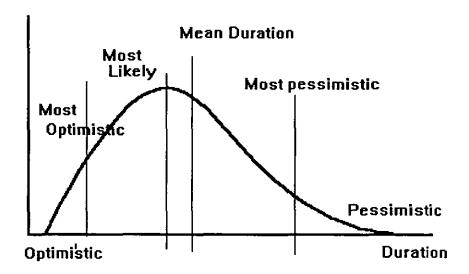


Fig. 2.4 PERT Graph

$$D = 0.2T_o + 0.6T_m + 0.2T_p \qquad (2.30)$$

$$SD = 0.2(T_o + T_p) \qquad (2.31)$$

where D is Activity Duration, SD is the Standard Deviation, T_o is the optimistic duration, T_m is the most likely duration, and T_p is the pessimistic duration.

Lichtenberg(1981) also suggested that fuzzy set theory could be applied in the uncertainty quantification in determining activity duration.

D. Dynastrat Model

Carr(1991) proposed the Dynastrat simulation model to predict the progress and cost of construction projects affected by uncertainties. The model consists of several modules. The interdependent random-variables sampling module is reviewed below. To calculate an activity duration with this module, using uncertainty variables, the following equations are used to adjust the standard productivity rate.

Daily progress = Crew Standard Productivity \times DMF \times WCF(2.32) where DMF is Duration Modifying Factor, WCF is Weather Correction Factor.

The *DMF* is calculated by using the following equation:

The value of DI is subjectively determined by planner taking account of susceptibility of an activity to the given set of factors.

P is obtained form the following equation:

$$P = (M_1 \times M_2 \times ... \times M_n)$$
 where M is multiplier. And M is calculated by:

$$M = I + R \times I$$
(2.35)
where R is rate of factor, I is impact on standard productivity.

Example:

Suppose that the site conditions for an activity j are measured as 5% below the normal conditions. And the impact of the site conditions on a crew productivity is shown to be 60 % higher than the standard productivity.

Factors	Rate of Factor (R)	Impact on standard productivity(I)	Modifier(M) $M = 1 + R \times I$
Site Condition	below 5% = 0.05	60% Add= (1+0.6)=1.6	1 +(0.05)(1.6)=0.92
Management	above 10% = 0.1	40 % discount =(1-0.4)=0.6	1+(0.1)(0.6)=1.06

Table 2.3 Modifier Calculation

From this information, the value of M for these site conditions is calculated as 0.92. This represents a productivity rate 8% below the standard productivity rate. The same procedure can be applied to the management factor resulting in the modifier, M. being 6% above the standard productivity rate. Activity j, say the laying of the outside skin of a cavity wall, is affected by both factors. And each activity also has unique degree of impact(DI) which is assumed to be 1.10 for this case, since the bricklaying activity as mentioned above is susceptible to the two factors. The Duration Modifying Factor(DMF) for the activity j, resulting from the site conditions, management factor and DI can then be calculated as:

DMF =
$$0.92 \times 1.06 \times 1.1 = 1.073$$

Once the DMF value is determined, the next task is to define the Weather Correction Factor(WCF) value. Assuming that the weather conditions are not as good as those defined as normal weather conditions, WCF is assigned a value of 0.9. Then the adjusted productivity can be calculated as:

Adjusted productivity = $1400 \times 1.073 \times 0.9 = 1352$ bricks/day

Note: Standard productivity is assumed to be 1400 bricks per day.

This model requires too much subjective information about the values of Modifier, DI and WCF. It appears that this system is quite difficult to use without pre-established standards against those parameters used in the system.

2.3.3 Expert System Approaches

Birrell(1980) and other researchers(Levitt 1985, Gray 1986,1987, Hendrickson 1987, Ibbs et al.1989a) have noted that human heuristic knowledge plays an important role in many complex and dynamic systems analysis within the civil engineering domain. Recently, researchers have attempted to capture and formalise the expertise of construction planners used to determine activity durations. It appears that knowledge based system approaches which employs heuristic knowledge are more promising than other methods for determining activity duration. Some examples of this approaches are described below.

A. Hendrickson Model

Hendrickson et.al.(1987) proposed a proto-type expert system named 'Mason' for determining bricklaying activity durations. They proposed the following equation, introducing the "down time" concept for the factor adjustment.

$$T_K = \frac{Q_K}{N_K \times P_K} + \frac{D_K}{N_K} \qquad (2.36)$$

where, T_k = the duration of activity k, in hours or days,

 Q_k = the physical quantity of work required for activity k,

 N_k = the number of crews working on activity k,

 P_k = the estimated productivity per crew on activity k, in units of work per hour or day,

 D_k = the estimated idle or downtime during the activity duration for set-up and other activities, in hours or days.

As shown in EQ.2.36, determination of the two variables, P_k and D_k , are the main tasks in this system. For the determination of P_k , they suggest the use a two stage estimation processes. First, the maximum productivity of an activity is estimated based on the ideal working conditions. Next, this maximum productivity is discounted according to various factor's conditions. For the adjustment process, a number of expert rules are established in the form of a causal relationship, i.e. if a particular conditions exists, then reduce productivity by x %. For example, if temperature is above 85° F, then the productivity might be reduced by 10 %. In this way, P_k can be determined. Finally, for the downtime estimate, D_k , this is done by simply aggregating the durations of the various extra work items such as insulation, DPC, anchoring work, etc..

The execution of Mason employs a 'backward-chaining' inference strategy. For example, when solving the goal 'estimate activity duration', Mason creates sub-goals 'estimate productivity' and 'estimate downtime'. This procedure is continued in a 'bottom-up' fashion until the original objective is achieved. This system is implemented in the OPS5 programming language. The overall estimation hierarchy is shown in Fig. 2.5.

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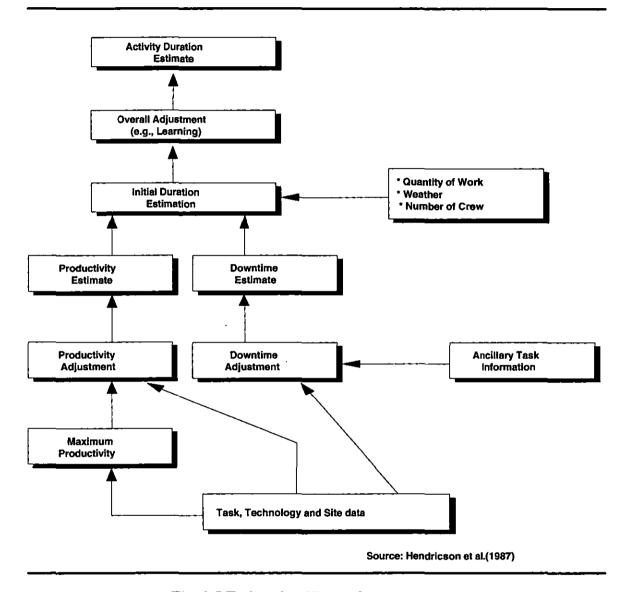


Fig. 2.5 Estimation Hierarchy

The accuracy of this system relies entirely on the subjective definition of the % discounts to be used in the expert rules. This is likely to result in inaccuracies, as the elicited expert rules are not going to be 100% accurate. This problem is not unique to this system, i.e., most expert systems have the same difficulty with the reliability of rules. This is due to the expert being unable to provide totally objective and accurate values for the uncertainty factors. For this reason, the authors of this system suggest that the fuzzy set theory can be

used to enhance this problem, i.e., a rule can use more relaxed discount percentages which will in turn allow for the use of linguistic terms rather than using single numerical value.

B. Herbsman Approach

Herbsman et al.(1990) proposed a prototype expert system. This system can be applied to the activity cost monitoring and control, with particular reference to highway projects. This expert system employs frame based knowledge representations to implement the structured expert knowledge. The estimation hierarchy with reference to the mason project is shown in Fig. 2.6.

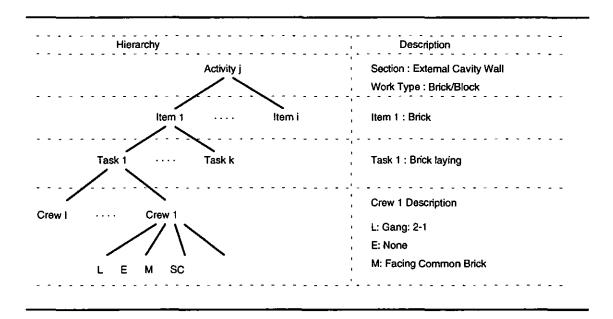


Fig. 2.6 Estimation Hierarchy

The method for producing activity durations and costs is as follows. First, the data for a standard crew is obtained form an historical data base containing productivity rates and unit costs for labour, material, equipment and subcontractors, for typical activities of highway project. Next, the estimation of durations and costs is started at the lowest level, and proceeds up the hierarchy. The knowledge used in this system is derived from the

historical data base and stored as a rule-set for each typical activity. The following are the example rules used in this system.

Rule 0045: IF Laser-grading apparatus is used

Then Adjust unit price by 1.35 times.

Rule 0048: IF Unit price adjustment for Equipment crew exceeds 1.15

Then Replace the costliest equipment in the crew configuration.

etc.

C. Kähkonen Approach

Kähkonen(1989) and Tyrvainen(1990) developed a knowledge based system called 'Ratuaj' for determining duration of site activities in building work. The Ratuaj is also structured hierarchically, and combines lower levels of work task duration into a higher level activity duration. The core of this system is the Ratu-production file which consists of productivity leaflets called 'Ratu-cards'. The files have been developed over a period of 15 years in Finland and currently cover almost all critical activities in typical project schedule and about 70 % of the labour cost of a project(Kähkonen 1989). The file contains very comprehensive information on working methods, unit times, material rates and other related factors(Tyrvainen 1990). The activity duration is built-up from those components of the work task which fall below the activity in the hierarchy. Fig. 2.7 shows the estimation hierarchy.

The development environment of this system consists of an expert system shell, NEXPERT, running on a Macintosh II microcomputer. Microsoft's Excel spreadsheet program is also used for data analysis.

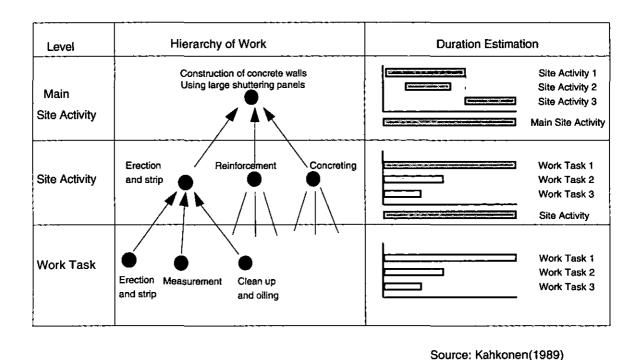


Fig. 2.7 Hierarchical Estimating Approach

2.4 Summary

Estimating activity duration is subjective and experience based due to the complexity and uncertainties involved. The various studies aimed at developing models for activity duration were examined in this chapter. Most of the studies have concentrated on adjusting productivity rates in order to take account of the various factors in determining activity duration. No unified method can be found, i.e., different people use different methods for determining an activity duration. This is due to the difficulties in determining a productivity rate subject to a wide range of influencing factors. This suggests that further investigation is required to enhance the current approaches in modelling activity

duration. This study forms part of that work by examining the applicability of fuzzy set theory to the activity duration estimation domain.

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3.1 Introduction

This chapter outlines a broad perspective to formulating the basic concepts for an activity duration/cost modelling approach. The main purpose is to propose the need for a fuzzy heuristic modelling concept. This chapter begins by identifying and assessing the four components of the activity production system. Form this, the causal relationship which will be used to capture an expert knowledge is defined. The chapter then presents the research concept by examining the problems associated with this casual relationship.

3.2 Activity Production System

The system under consideration in this study is the activity production system. The activity production system is defined here as the process of converting resource inputs into the completed building components. An activity is defined as an action of converting resources inputs to an end product which is a building component(A more detailed activity definition is presented in chapter 4). An activity changes the system from a state S1 to a state S2, thereby changing its value from V1 to V2, and consuming the time from T1 to T2, as shown in Fig. 3.1.

An activity is carried out by a gang(crew) and controlled by a site manager. If it is an automated activity, as in a mass production process, the operative is possibly working with a robot which has an 'intelligent' control mechanism. Sensors can then identify the initial and final states, S1 and S2, and m the progress between these states, and react to any unexpected changes(Knoepfel 1989). However, the environment in which a construction activity is performed is completely different to that in which mass production takes place.

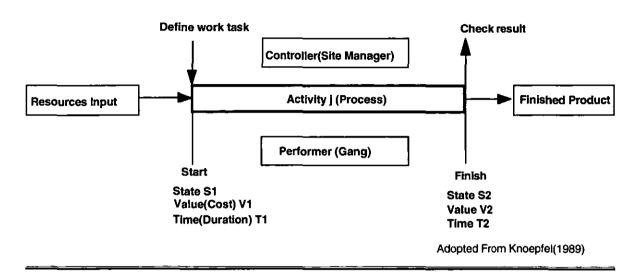


Fig.3.1 Effect of an Activity

The progress and outcome of a construction operation process is subject to a wide range of uncontrollable and controllable factors. Consequently, the production unit rate of an activity is also subject to the design aspect, physical job conditions, management efficiency, etc.. The influence of these factors causes uncertainties in the determination of activity duration/cost. With this view, the activity production system can be illustrated in Fig 3.2.

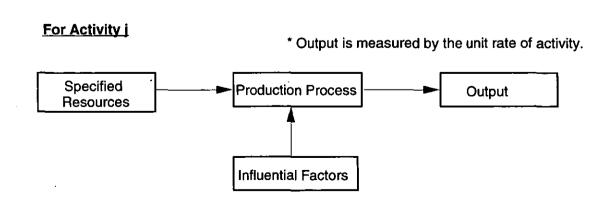
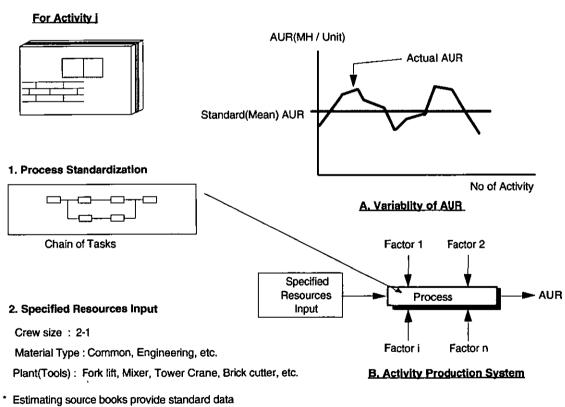


Fig. 3.2 Activity Production System

As a starting point to investigate the modelling of a system, Koofman(1977) observes:

"modelling a poorly understood system cannot represent a reality. If a model does not reflect some real understanding and insight about the system, it is probably useless."

With this perspective, each component should be clarified to understand the system under investigation. In order to examine the system, Fig. 3.2 can be restructured in more detail as shown in Fig. 3.3. To illustrate the system, a hypothetical external brick wall activity is used.



3. Influential Factors

Weather condition, Site condition, Buildability, Management, etc.

Fig. 3.3 The Variability in AUR

3.2.1 Process

The process refers to the sequence or chain of tasks which are needed to convert resources input to an end product. The process can be viewed as an assembly line to produce a product. A process consists of a number of tasks which represent the action of installation of several parts for a specified building component. For example, the process for building an external-brick/block-cavity-wall is represented by a linear sequence of work tasks such as brick/block laying, mixing mortar, insulation, DPC, etc..

The determination of the sequence of tasks is normally dictated by design features. However, unless the activity is an innovative type, the process to construct a building component can be considered a standardised process. In this study, the main concern is to examine how the impact of factors on the pre-defined process can be most accurately quantified.

3.2.2 Specified Resource Inputs

The resource inputs are a specific set of resources which are needed to construct a building component. These are shown in Fig. 3.3. Material types and building component shapes are dictated by design(drawings) and specifications. Working method, crew size, work sequence, gang composition and plants selection etc., are normally based on the contractor's preferences for managing a job. There will be many constraints and limitations on the combination of these resources. These are the contractor's organisational capability, their management style, surrounding environment, etc.. These constraints will dictate the combination of resources input for each specified activity. Simulation techniques such as CYCLONE(Halpin,1973) may provide a tool for optimising the combination of resource

inputs. The search for the optimum composition of the resources input is not addressed in this study.

The effect of different combinations of resources input for the same activity can be defined from existing estimating sources in terms of a standard unit rate. Thus, different combinations of resource inputs for the same activity can be represented by the standard AUR(This will be addressed in chapter 4). The prediction of AUR in this study is based on the specified resources input for the specified activity under the influenced a given set of factors.

3.2.3 Output

The output of a system is directly related to the cumulative effect of all the factors impacting on the production process. The Activity Unit Rate(AUR) is used as a measure of the output resulting from the influence of the factors. As shown in A in Fig 3.3, AUR fluctuates widely. Theoretically, if an activity is carried out in a controlled environment like, an automated mass production environment operated by a robot, then there is no reason why the same AUR should not be achieved for the future same activity. However, this scenario cannot be applied to the construction industry, since a construction production process is subject to numerous variables and many of them cannot be controlled by the contractor. The effect of factors results in declining or increasing AUR, i.e., variability in AUR. In this study, the only causes of variations in AUR considered will be limited to these of the influential factors.

3.2.4 Influential Factors

A. Classification of Influential Factors

There are numerous factors which cause the variability of AUR. These causes are generally termed as influential factors. Broadly speaking, the influential factors can be grouped into two categories: quantitative and qualitative ones. The quantitative nature factors are those which are countable directly by observation. For example in a bricklaying activity, wall thickness, gang composition, wall height, temperature and humidity, etc. belong to this category. The quantification of the impact of these factors on activity is governed by the law of statistical theory in conjunction with work study techniques.

On the other hand, the qualitative factors are those which can not be measured objectively in terms of the impact measurement on an activity and the degree of factor measurement. Factors belonging to this category include crew motivation, the efficiency of management control, complexity of the design aspect, weather condition, site condition, etc.. The effect of these factors on an activity can not be quantified objectively, instead they are qualified(Ayyub and Haldar 1984). For example, future weather conditions that affect an activity can only be measured as good or bad, etc. since there is no standard acceptable numerical value attached to this qualitative measurement.

The nature of factors used in this study are those related to the qualitative nature. Thus, the factors under consideration in this study are referred to as Qualitative Factors(QF).

B. Identification of Factors

For the system analysis, the important factors must first be identified. Then the causal relationship can be determined. Practically, only a very few factors and simple relations are needed. After a system is verified and validated with these factors, then the system can be

generalised to other similar types of factors. With this view, the factors considered in this study are shown in Fig. 3.4.

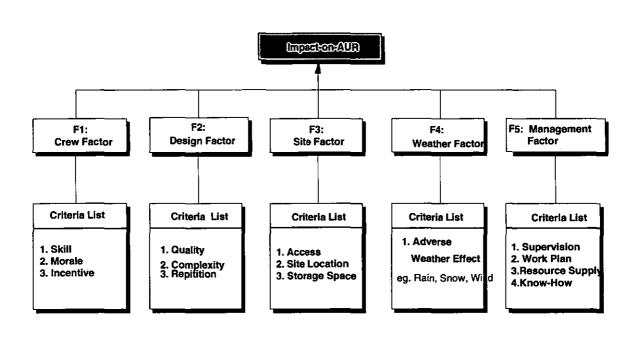


Fig. 3.4 Factor Grouping

For brevity, the various criteria list are grouped collectively under a factor heading. Generally, these factors can be identified by observation, research findings and interviews with practitioners. These factors as shown in Fig.3.4 are frequently used in the labour productivity studies (Thomas et al.1987, Sanders 1989, Horner et al. 1990). More detailed description of these factors is presented in Sanders (1989). Although, it is easy to generate a list of factors, it is difficult to quantify them. These factors are chosen for a fuzzy rule based system, FAURA, developed in this study to demonstrate and test its feasibility (refer chapter 5). However, other similar factors can be added or deleted as necessary.

3.3 Causal Relationship

3.3.1 Definitions

The variability of Activity Unit Rate(AUR) can be explained by using a cause and consequence relationship(causal relationship). A cause is, in general, defined as the source of influence on an object which will be referred to as a factor in this study. The definition of a factor is the set of hypothesised causes which have influence on an object. Influencing is a general term to denote that a factor can have a positive or negative impact on an object. An object could be at project level, WP level, activity level or task level, i.e., relative to the level of detail of analysis. In this study, activity level is used as the object. A consequence is a result of the degree of influence on the object. This is shown in Fig. 3.5.

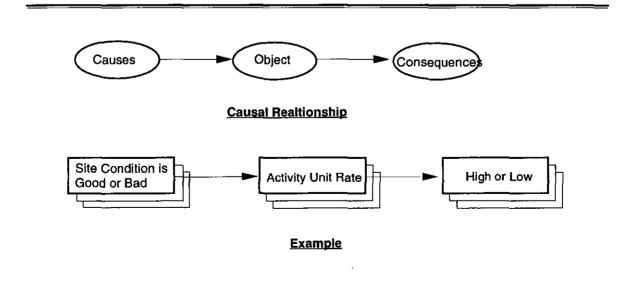


Fig. 3.5 Causal Relationship

3.3.2 Formalising Causal Relationship

With the causal relationship definition provided in the previous section, the knowledge relating to the cause and consequence relationship, i.e., factors and AUR, can be established in the form of an 'if ... then ...' conditional statement. This conditional statement is referring to a production rule. If the values of premise and conclusion of a rule are linguistic terms, then it is called the fuzzy production rule. Thus, using the fuzzy production rule format, knowledge relating to the causal relationship can be established. For example, the causal relationships can be established into fuzzy production rules as:

If site condition is **bad** Then AUR is **high**If weather condition is **good** Then AUR is **low**Etc.

or in general,

where Ai represent the value of degree of factor, Bi represent the value of susceptibility.

In EQ.3.1, the two terms which are the Degree of Factor(DF) and susceptibility are used to measure the cause and consequence.

Fig. 3.6 shows these two terms.

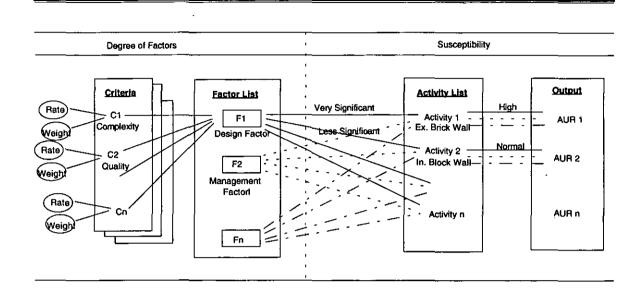


Fig. 3.6 Causal Relationship Concept

The following sections explains these two terms used in the causal relationship.

A. Degree of Factor

The term Degree of Factor(DF) is used to measure the degree of a factor. The existence of factors and their criteria list can be identified from various sources such as drawings and site visits, etc.. However, it difficult to measure the DF objectively, since there is no standard available. In such case, the DF is measured in linguistic terms, rather than mathematical terms. For example, factors can be measured as good or bad weather, complex or easy design aspect, etc.. For this reason, in the past, different people have used different techniques for the measurement of factors. Horner et al(1987), Olomolaiye(1990) and Russell et al.(1990) have used a subjective factor measurement technique by applying rate and weight of each criteria in a factor. Another promising method which can be applied in factor measurement is the Fuzzy Weighted Average(FWA) method proposed by the Dong and Wang(1985,1987). Appendix A

summarised this technique in detail. Thus, using these techniques, it is possible to measure the degree of factors in a fairly objective manner.

B. Susceptibility

The sensitivity to which output(AUR) is affected by the influence of the degree of a certain factor is dependent on the nature of an activity. This sensitivity is referred to as the *susceptibility*. Susceptibility is used to measure the factors influence on AUR. Measuring the degree of susceptibility objectively in a precise term is difficult, since it is not clear what factors the AUR really depends on and to what degree. The experienced planners(or site managers) use linguistic terms to estimate the susceptibility. For example, the susceptibility on a certain activity to any of these factors is measured in linguistic terms, e.g. *highly* susceptible, *strong* influence, etc.. Then the major problem lies with the interpretation of the linguistic terms used by the experienced planners. The linguistic terms can be translated into mathematical measures by fuzzy sets theory(refer chapter 2). In this study, linguistic terms are used to measure the susceptibility, and these are then incorporated into fuzzy sets.

3.3.3 Assumptions

In order to establish the causal relationship rules, the following assumptions are required.

A. Factor Interdependency

In this study, it is assumed that all factors are not interdependent. Consider the degree of a crew skill which is evaluated as 'good' by one's judgement or by a factor measurement mechanism during the initial planning stage. It is assumed that this value is not dependent

on any other factors. In other words, once a crew skill is evaluated as being good, it will not be affected by any other factors such as site condition, weather, etc. Some level of interdependency may exist between them. However, for the simplicity of modelling the causal relationship, it is assumed that all factors used in this study can be treated as independent from all other factors.

B. Predictability of Factors

Factors can be classified into two group according to the predictability of their occurrence. These are the deterministic group(predictable factors such as site condition, complexity of design, etc.) and the non-deterministic group(unpredictable factors such as weather, crew skill and management control, etc.). The deterministic factors can be evaluated reasonable accurately during the initial planning stage by examination of drawings and site visit ,etc.. Assuming the design does not change, for example, these value can be considered as constant. i.e., there will be no changes of these values until an activity is finished.

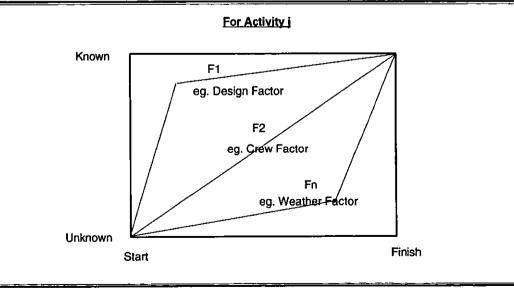


Fig. 3.7 Predictability of Factors

On the other hand, for the non-deterministic factor group, the chance of occurrence(probability) can not be identified in the early planning stage. For example, it is almost impossible to predict the weather conditions, or a crew skill at a particular time in the future during the initial planning stage. In such cases, it is assumed that the probability of occurrence of these factors can be reasonably anticipated by the application of heuristic knowledge(Thomas 1990). Based on this assumption, prediction of AUR can be undertaken in a deterministic way, i.e., the prediction is based on the existence of factors with known degree. Thus, all factors considered in this study are assumed to be deterministic.

C. Factors Interaction

The output(AUR) is the consequence of interaction by many factors. It is difficult to measure how much a specific factor with a certain degree contributes to the particular AUR. Actually, it can be measured as many factors-to-one unit rate(in short many-to-one) relation. However, this relation can not provide any useful information for a factor analysis, since it does not contain any information as to a specific factor's contribution to a unit rate. Thus, when establishing a causal relationship, it should be a one-to-one relationship. This is based on the *ceteris paribus* assumption that when we consider one factor influence on an output, the other factors are considered as constant, which is an average condition in this study(Flanagan et al. 1987). This assumption is critical to formulate a rule base(refer section 6.2 chapter 6). Thus, in this study, it is assumed that an expert can provide the one-to-one causal relationship in the form of a fuzzy production rule based on the *ceteris paribus* assumption.

3.3.4 Need for Heuristic Approach

A. Problems in Statistical Approach

The problems associated with a statistical approach can be examined by observing the variance between actual AUR and Standard AUR(SAUR). The variance analysis is normally used to measure the efficiency of performance in productivity analysis. This can be expressed as:

$$Variance(V) = \frac{Actual \ AUR}{Standard \ AUR} \dots (3.2)$$

where the Standard AUR can be derived from published estimating sources or companies own records, and this is a constant parameter. The variance, V, can be used as a measure of the overall factors influencing a specified activity. A value of V above unity indicates that factors are having a negative influence on the activity unit rate(AUR), and vice versa. The actual AUR is the consequence of interaction by many factors such as management efficiency, site conditions, weather conditions, design aspects etc.. The V value represents the fluctuation in AUR due to the different level of factor involvement for the same activity. This is shown in Fig.3.8(a).

To construct this variability curve is simply a matter of data collection. However, in order to explain this fluctuation, the causal relationship curve(see Fig.3.8(b)) is essential, since this can explain what causes will change the AUR and by how much. The hypothetical causal relationship curve is shown in Fig. 3.8(b). The X axis represents the degree of factor i, i.e., cause and the Y axis represents the susceptibility of the activity to the factors. Thus if we can collect the causal relationship data, it is possible to develop a statistical model through regression techniques. However, in reality, it is extremely difficult to collect sufficient data to yield a statistically sound regression model.

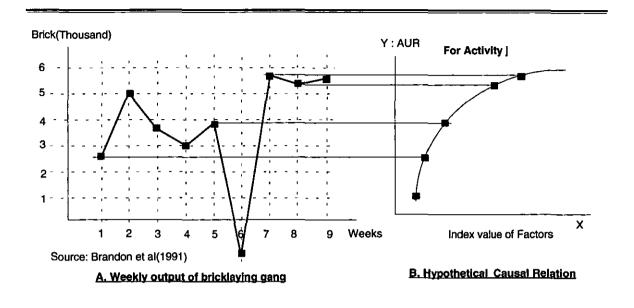


Fig. 3.8 Variability of AUR and Causal Relation

For example, the unit rate of a brick/block wall activity is subject to a wide range of factors. The relationship between these factors and Activity Unit Rate(AUR) are very complex since it is not clear what factors the AUR really depends on and how much these factors impact on AUR. Further, the impact of these factors on an activity can not be measured quantitatively, but only in qualitatively(refer Ayyub and Haldar 1984). Horner et el.(1987) observed this problem and states:

"the factors on which productivity is dependent are not easy to isolate, much less measure, and interdependencies are complex. Nor is the measurement of productivity itself straightforward, not least because of an inherent, unpredictable variability in the level of human performance."

These difficulties are compounded into data deficiency problems when attempting to model the causal relationship by statistical approach. Hence, it is difficult to use statistical techniques to model the causal relationships, since there is neither a clear way of measuring causal relationships nor can we set up an experiment with a controllable

environment to collect sufficient data to yield an objective solution. For this reason, in the past, most labour productivity models exclude the qualitative factors impact.

To overcome these problems in the establishment of the causal relationship, an heuristic approach can be used to provide a subjective solution.

B. Need of Heuristic Approach

Birrell(1980) states the importance of an heuristic approach for particular construction process planning and control issues as:

" an heuristic analysis of a construction process is the best starting point of the search for a sound concept of the construction process. This heuristic concept of the construction process is a model that is simple, strong, realistic, optimally cheap to use, but unfortunately not written down. It is realised by those people who are, or have been, involved in actual construction management."

Many researchers(Flanagan 1982, Ayyub et al 1984, Gray 1987, Handrickson 1987, Brandon 1991) support the view that knowledge gained from experience plays a very important role in decision making due to the absence of information/data about cause and consequences relation. For example, an heuristic rule ' if site conditions are bad then AUR is likely to be within a certain range' represents this case. This subjective judgement in a causal relationship is based on the state of mind. The accuracy of subjective judgement is dependent upon the present state of knowledge they posses. To prove the accuracy of the judgement is subject to the individuals perception and state of knowledge, i.e., different people may have different estimations of value. The justification for using a subjective judgement can be due to the bias involved in that process. However, such criticism can be easily overcome by understanding that the judgement about a casual relationship is precisely the kind of knowledge that planners or estimators have been using

in many years of practical experience. In addition, these kinds of judgement will improve as more information/data is gathered as time goes by. Flanagan et al.(1987) strongly support this view of using subjective estimates. Accordingly, it is necessary to have a systematic approach to reduce bias and to have more formalised way of dealing with subjective matter.

However, it should be emphasised that heuristic approaches can only be applied in certain areas. For example, it is not necessary to use this approach for simple and measurable causal relationships, where a statistical regression approach is more appropriate. For a highly repetitive and heavy equipment oriented production process, a simulation approach can yield the best solution. For uncertainty situations where there are no clear methods of measurement for causal relationships, or in the absence of a widely acceptable model, the heuristic approaches can produce the best practical solution. In summary, each approach has its own strengths and weaknesses. Therefore, the selection of a modelling approach is dependent upon a given situation. In this study, the heuristic causal relationship modelling approach is selected.

3.4 Research Concept

This section presents the research concept to formalise the application of an heuristic approach for the determination of activity duration/cost.

3.4.1 The Predictability Concept

Our inability to quantify the impact of the various factors on the crew's performance in the planning stage is reflected in the variance analysis as shown in Fig. 3.9.

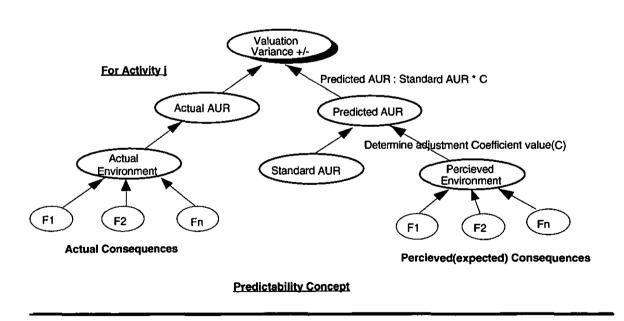


Fig. 3.9 The Predictability of AUR

Theoretically, if the adjustment coefficient value (C) under a given set of factors is known, then it is possible to predict the most like AUR which implies an Adjusted AUR(AAUR). For a particular activity j, the Adjusted AUR(AAUR) can be expressed as:

$$AAUR = Standard AUR(SAUR) \times C \dots (3.3)$$

In this case, the C value implies an adjustment coefficient against the SAUR. In other words, the C value represents the impact of factors on a specified activity in question. Thus, it is clear that, from EQ. 3.3, if we know the SAUR and C value for an activity j, then it is possible to predict AUR for that activity. However, there are two problems in determining the AAUR which are (1) how to determine the standard AUR for a specified activity; and (2) how to determine the value of C under the given factors influence. The following section will discuss these problems.

A. Generating Standard AUR(SAUR)

The SAUR refers to the average unit rate of an activity. The SAUR implies that an activity is performed under normal conditions, i.e., all factors having an average value. The SAUR can be extracted from existing estimating data bases such as Wessex(1990) and Spon(1988), etc. since the production unit rate in the publishing estimating sources reflect nation-wide average productivity rates. Once the SAUR for a specified activity is defined from these sources, this value is then used as the standard value for the factor adjustment process. However, there is some difficulties in generating SAUR, since an activity usually consists of several operations which have their own unique unit rates. This creates some problem when combining various unit rates into one representative unit rate, i.e., AUR. Chapter 4 discusses the method of generating SAUR in more detail.

B. Determination of C value.

The determination of the C value relies upon a large data base that contains data generated from a wide range of project conditions. This not only requires a standardised data collection method to ensure consistency, but also needs accurate data. However, there are several problems in determining the C value in an objective way. This was mentioned in

section A in section 3.3.4. Thus the determination of the C values has to rely on heuristic expert knowledge. The justification of using heuristic knowledge is explained in section B in section 3.3.4.

3.4.2 Causal Relation Rule Mapping Concept

This section discuss the concept of casual relation rule mapping. The causal relationship can be established by the fuzzy production rule format as described in EQ 3.1 in section 3.3.2. The fuzzy rule can be explained using graphical presentation as shown in Fig. 3.10.

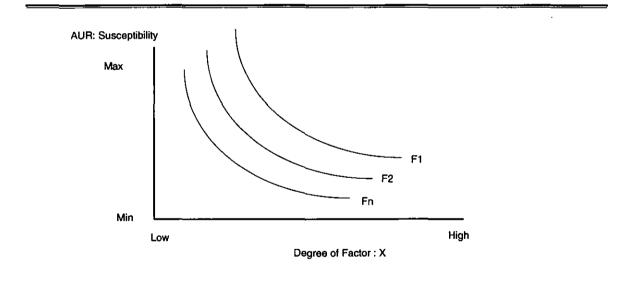


Fig. 3.10 Rule Mapping Concept

The X axis represent the degree of factors. The Y axis represent the susceptibility in AUR. Each line in Fig. 3.10 represents rules for a particular factors. Thus if we have n factors, it requires n causal relationship lines. The reason for having a unique line for each factor is due to the relative degree of impact on an activity. This means that even though, all factors have the same degree, one factor can impact more significantly than others.

This curve is used to show the concept that if degree of factors are increased or decreased, then their corresponding AUR will be increased or decreased respectively as a result. This causal relationship can be established with the help of experts.

3.4.3 Fuzzy Causal Relation Concept

With the rule mapping concept as described in the previous section, the rule mapping can be explained as follows.

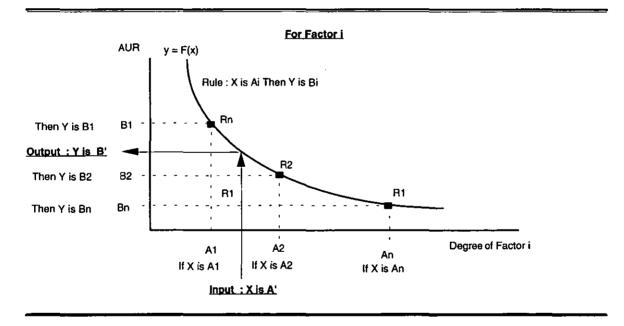


Fig. 3.11 Causal Rule Mapping Concept

Referring to Fig. 3.11, a rule can be defined in terms of reference points R1, R2,..., Rn, on the line based on his/her judgement or with the help of experts. In this case, each point on the fitted line implies a rule. The scale of the X and Y axis are actually represented by linguistic terms(Fuzzy sets), i.e., a range. Each point in the fitted line implies a rule, thus this line implies the collection of rules which is a rule base. The purpose of this graph is to

explain the concept of the fuzzy logic (Zadeh 1975b, 1975c, 1976, 1978, 1983). The function of the fuzzy logic is to deduce an output for the given input value from a common body of knowledge which is a rule base. Assuming that a data base of rules is collected from experts, then prediction of AUR can be made by using fuzzy logic. More specifically, if we have a line y = F(x) which implies a rule base as shown in Fig. 3.11, then, it is possible to deduce y = B' from given input x = A' and y = F(x). The formulation of the fuzzy rule based system for the AUR determination employing this technique is discussed in Chapter 5.

3.5 Summary

In this chapter, the followings subjects have been discussed.

A. Modelling Limitations

- The effect of resources allocation on AUR is not considered.
- Process related variation in AUR is not considered.
- Only qualitative nature of factors are considered.

B. Modelling assumptions

- All factors are assumed to be independent.
- The chance of occurrence of factors is assumed to be deterministic.
- Factors interaction on AUR is assumed to be separable based on the *ceteris paribus* assumption, thus it is possible to establish one-to-one casual relationship.

Based on the modelling limitations and assumptions listed above, the research concept is proposed in this chapter. To design a reasoning system for determining activity duration/cost, the two essential tasks of generating Standard AUR and an adjustment mechanism have been identified in this chapter. The following two chapters aim to formulate these tasks. Chapter 4 presents the method for generating Standard AUR. Chapter 5 presents a mechanism for adjusting AUR in the form of a fuzzy rule based system.

Chapter 4: Generating Standard AUR

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4.1 Introduction

In the previous chapter, the need for a Standard AUR is discussed. The scope of this chapter is limited to two aspects which are; (1) a formalised method for identifying and defining activities, and 2) a formalised method of generating Standard AUR. A typical external brick/block wall has been used as an example activity. However, the principles used in this chapter can be extended to other types of activity.

4.2 Work Breakdown Structure(WBS)

From given design information, activities must be extracted in appropriate size to suit the level of detail used in the scheduling methods. This requires that a project needs to be broken-down into an hierarchical manner so that a suitable number of activities which satisfies the level of detail needed by the user can be defined from this structure. This hierarchy refers to the Work Breakdown Structure(WBS). Thus, using the WBS, a project can be structured in a hierarchical manner so that an activity can be identified.

For the efficiency of scheduling, determination of an appropriate level of detail of activities appears to be of most concern. For example, if an activity is defined in too much detail such as cut brick, mix mortar, laying brick, etc., it will be a mass of detail which is not efficient and is impractical to use in scheduling tools. On the other hand, if an activity is defined too broad such as construct brick/block wall, construct foundations, etc., then this results in little benefit when used for project control and monitoring. Thus, the determination of level of detail for an activity used in scheduling is dependent upon the scheduling purposes required by a user such as for tactical, strategic or operational

purposes. Hence, the level of detail of an activity used in scheduling could be a work package, activity or task level of detail.

The typical well known breakdown of a project is Project - Work Package - Activity - Task. This shown in Fig. 4.1.

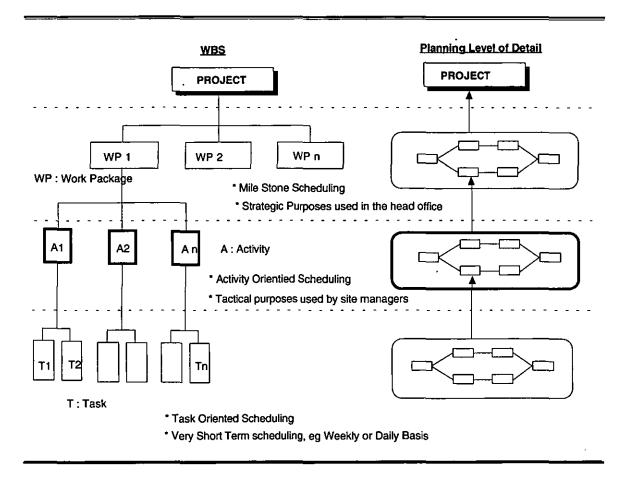


Fig. 4.1 The Work Breakdown Structure of Project

This is a 'top -down' approach. First, a contractor evaluates a project from a broad perspective in the tendering stage for strategic purposes. This is the pre-tendering stage project scheduling. In this stage, WP level is generally used as this stage does not requires detailed scheduling. When a contractor wins a bid, a detailed schedule can be developed.

In this stage, activity oriented scheduling is needed for tactical purposes. Finally, task oriented scheduling can be developed for very short term planning such as weekly or even daily basis for operational purposes. This study will concentrate on the activity level of detail. Based on the activity oriented schedule, it is possible to generate a more detailed schedule.

4.3 Definitions and Terminology

4.3.1 Activity Definition

A number of definitions of activity have been presented in literature(Halpin and Woodhead 1976, Gray 1985, Willis 1986, Eldin 1989, Ibbs 1989b). This reveals many different meanings given to it by different people. The term 'activity' has been used to represent various aspect of work such as design activity, construction activity, scheduling activity, site activity, operation, WP, Task, etc.. The main concern in this section is to define a general term 'activity' used in scheduling methods.

An activity is primarily composed of two distinctive features, namely building component and the operation. Ibbs et al.(1989b) described activities as:

"Activities are the elements that represent the actions of installing the building components. The concept of installing a building components is here generalised to include any action of placing, removing, modifying or testing the building components. Activities associate the particular task of installing a component with a particular crew and the required equipment's."

This definition can be explained in more detail as shown in Fig. 4.2. which contains the three types of information: 1)building component, 2)work section and 3)operation so as to clearly pinpoint the physical building component along with a specific work section and the type of operation required for installation. Also, the activity can be defined as a time and resource consuming event for the installation of a building component for the specified work section used by planners for time and cost control purposes.

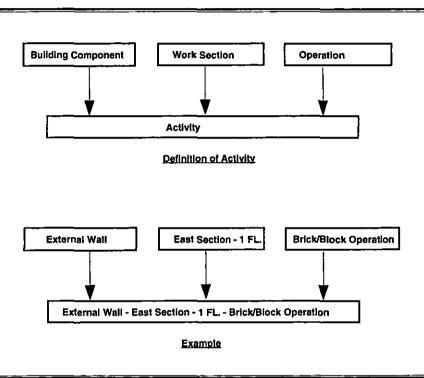


Fig. 4.2 Definition of Activity

4.3.2 Task Definition

A building component usually consists of several parts, and hence the operation needs to be broken-down into the constituent components for the installation. For example, an external brick/block wall might consist of several parts such as DPC, wall ties, insulation, etc. Each individual item associated with an activity also requires an operation for its installation. The installation of a building component's part is termed a 'task'. A task is generally a very specific, simple operation which will normally be of repetitive or cyclic nature, such as mixing mortar, laying bricks, stacking bricks, etc.. Each task has its own relatively short and unique duration with a start and completion time. The task level detail is used for the estimation of construction costs and for productivity analysis by work study techniques. An activity is the aggregation of a number of task items. The term 'task' is the bottom level of the WBS as shown in Fig. 4.1 in section 4.2.

4.3.3 Attributes of Activity

An activity is associated with: (1) a quantity which measures the volume of work in specified work section, (2) the unit rate of activity(AUR), (3) the activity duration, and (4) the activity cost. The activity has several attributes which need to be defined. These are shown in Fig. 4.3. The details of these attribute are discussed in section 4.5 and 4.6.

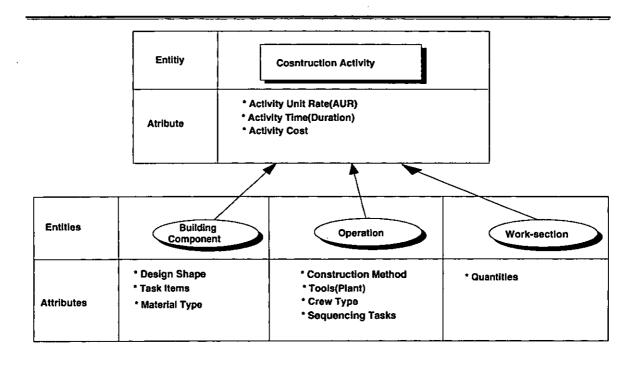


Fig. 4.3 Activity Attribute

4.3.4 Definition of Productivity

It is essential to examine the productivity rate(or unit rate) definition, since the AUR is derived from the productivity definition. The term productivity varies according to its application to different purposes. The widely acceptable definition of productivity has been examined by Thomas et al.(1990). They suggest the following productivity definition:

Labour Productivity =
$$\frac{Labour\ Cost\ or\ Work\ Hour}{Output} \qquad(4.1)$$

or more specifically,

$$Prouctivity_{i} = \frac{Man\ Hour(MH)}{Quantity\ of\ Work\ Item_{i}} \qquad(4.2)$$

EQ. 4.2 is also called the unit rate. The unit could be the number of bricks, square metres of wall or cubic metres of concrete wall, etc. It can be measured on a construction site by allocation sheets which show the MH(man hours) spent on the specified task by using EQ. 4.2.

4.3.5 Definition of Unit Rate of Activity(AUR)

An activity is usually composed of several different materials and tasks(work items) associated with them to fix the building components as mentioned earlier. An activity duration is the summation of task durations. In this sense, the activity duration can be calculated by:

$$D = \sum_{i=1}^{n} T_i$$
 (4.3)

where T_i is the duration of task i.

An activity can be broken-down to the task level and this is shown in Fig. 4.4. The AUR is defined as Man Hours(MH) needed to construct a unit work of an activity. This can be defined by:

AUR = Total Paid Time for Activity / Quantity of Activity(4.4)

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In this way, AUR only can defined after an activity is completed. An example is given as follows.

Example

Activity Name: External Wall - WS1- Brick/Block

Quantity

: 28.5 M²

Crew size

: 2-1

Total paid time(duration): 87 MH, 8.5 MH per day

Based on this information, AUR can be calculated using EQ.4.4:

 $AUR = 87 / 28.5 = 3.05 MH/M^{2}$

When AUR is defined this way a low value is more productive than a high value.

However, this definition does not provide detailed information about the nature of an activity. Thus EQ 4.4 can be described in more detail as:

$$AUR = \frac{\sum_{i=1}^{n} T_i}{AQ} \tag{4.5}$$

where T_i is duration of task i(i=1,2,...,n).

AQ is the Quantity of activity j. T_i can be calculated by:

$$T_i = \frac{TQ_i}{P_i \times N} \tag{4.6}$$

where TQ_i is Quantity of Task i,

 P_i is a crew task unit rate i,

N is a crew assigned to the task i.

In this way, AUR can be synthesised from existing estimating sources by identifying the number of tasks and their Quantities and unit rates(productivity) at the planning stage. EQ. 4.5 is based on the unit rate having the work volume i.e., output(M²) per unit Man Hour(MH). For example, if a crew produce 0.5 M² of brick wall per 1 MH, then unit rate is defined as 0.5 M²/MH.

Often, a productivity(P') is expressed as Man Hour per Unit of work(MH/Unit) which is the reciprocal of P. For example, if a crew spend 2 hours to complete 1 M² of brick wall, then the unit rate is 2 MH/ M². Using this definition, an task duration is calculated as:

$$T_i = Q \times P'$$
(4.7)

where Q is quantity of task i, P' is unit rate of task i. It will be seen that both task unit rate definitions are used for the activity duration calculation without particular preference. In this study, the man hour per unit of work definition is used to represent the activity unit rate(AUR).

Fig. 4.4 shows this process. As shown in Fig. 4.4, the AUR is computed from the bottom levels which are the tasks quantities and their unit rates. More detailed examples of the process of generating AUR based on EQ.4.5. is provided in Section 4.5.

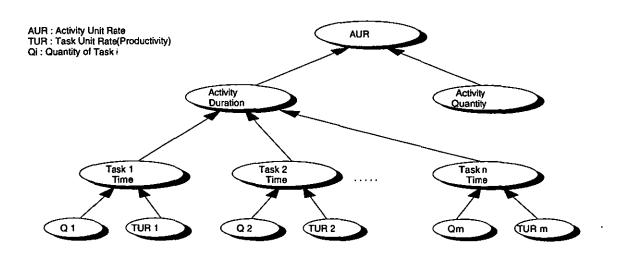


Fig. 4.4 Activity Unit Rate Hierarchy

4.3.6 Purpose of AUR

The constituents of an activity, i.e., number of tasks, differs form project to project. This is due to the uniqueness of design aspects, and hence it requires different combination of resources for the same activity. This uniqueness results in different AUR for the same activity. This prevents the use of a representative AUR for the same activity. Thus, AUR needs to be estimated each time for the same activity on each project due to the uniqueness of activity factors.

The purposes of using AUR in this study are twofold. First, AUR is used a standard value for the factor adjustment in the activity duration/cost estimation process. Consider site conditions as an example factor. Further, suppose an activity consists of number of tasks as shown in Fig.4.9. In this case, it is extremely difficult to measure how site conditions might influence the constituent of an activity such as DPC, laying brick/block, mixing

mortar, insulation etc.. Thus, for the factor analysis, it is logical to make a relationship between factor and activity level, rather than factor and task level relationship.

Second, AUR is made up of several different task unit rates. Thus, AUR is a unit rate which represents the various task unit rates associated with the boundary of the activity description. On the contrary, productivity rate represents the unit rate of the task itself. This is the difference between productivity rate and AUR. In this sense, AUR is a representative unit rate for an activity under consideration.

4.4 Identification of Activity

Ideally, the implementation of WBS would lead to the standardisation of structuring project information for planning and control purposes. In order to define an activity, a formalised hierarchical structure is required which can represent a project information structure. In this section, the method of identifying an activity is presented by using the WBS concept.

4.4.1 Previous Studies

The automatic generation of activity and sequencing has been investigated by many authors. Gray et al.(1985) defined the rules for the activity selection criteria based on the three criteria which are (1) types of work, (2) operationally significant function, and (3) operationally significant location. Further they identified rules governing the sequencing

between preceding activity and succeeding activity such as "covered by" or "embedded in" etc.. AL-Shawi et al.(1990) propose a proto-type system called "MIRCI" to assist in the generation and scheduling of construction activities. Their method of the identification of activity is based on the integration of the CI/SfB(Ray-Johns,1976) classification system and CAWS(1988). Zozaya-Gorostiza(1988) used the three tree structure consisting of (1) tree of design element for the building components identification, (2) tree of element activities for the operation identification, and (3) tree of project activities for integration of (1) and (2) structure for developing a proto-type expert system called "Construction Planex". This representation structure is based on the Masterformat coding system(CSI,1983). Garza(1988) used the concept of WBS for his semantic network in developing a proto-type expert system. The semantic network for identification of activities and generating activity list is based on CSI(1983).

However, these studies neglect some of the important principles about how to estimate activity duration/cost. For example, non of these studies have focused on how activity data can be synthesised in a systematic manner and how to deal with the various factor which influence activity duration/cost. These systems use the average productivity rates from the published estimating book to estimate activity duration/cost.

4.4.2 Representation Structure of Activity Identification

The representation structure for the identification of activities consists of the three breakdown structures shown in Fig.4.5. The integration of end items shown in Fig.4.5 as level 2, in the three structures yields the scheduling activity list. This enables project

information to be represented at a level of detail satisfying the different needs of planning, control and co-ordination of project. The following sections discuss these structures in more detail.

A. Building Components Breakdown Structure

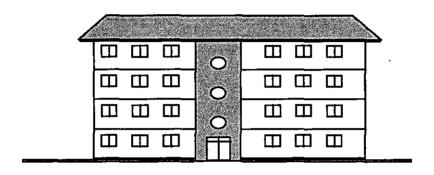
A building is composed of various components and their sub-components (elements). The break-down of building components into hierarchy is termed as Building Components Breakdown Structure(BCBS). The description of the components is usually described by the noun, for example, column, wall, foundation, roof etc.. The building components can be defined from the existing building classification systems, such as the CI/SfB(Ray-Johns 1976), Uniformat(Dell'Isola 1980), or SFCA(Refer Brandon et al 1991). These classification systems are intended for the design process prior to construction. The CI/SfB classification system is shown in Appendix B as an example of these classification systems.

B. Work Section Breakdown Structure(WSBS)

An activity should contain information about work section(location) of building components which will be constructed in a specified location by specified task team(gang). For example, if one uses an activity as 'External Brick/Block wall', then this does not provide any information relating to the volume of work and location of the component. It is not clear whether this refers to entire brick/block wall or 1st. floor wall. Thus, for the scheduling purposes, the building components needs to be broken-down into appropriate work sections. The work section provides three types of information which are critical in scheduling. These areas are:

Gang deployment

- Volume of work
- Activity sequencing



Elevation of Front

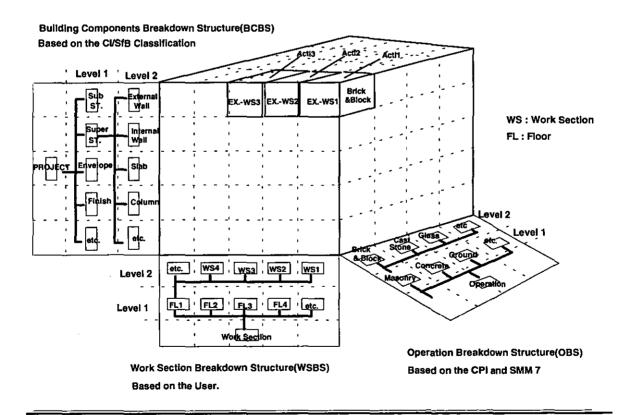


Fig. 4.5 3-D View of the Representation Structure

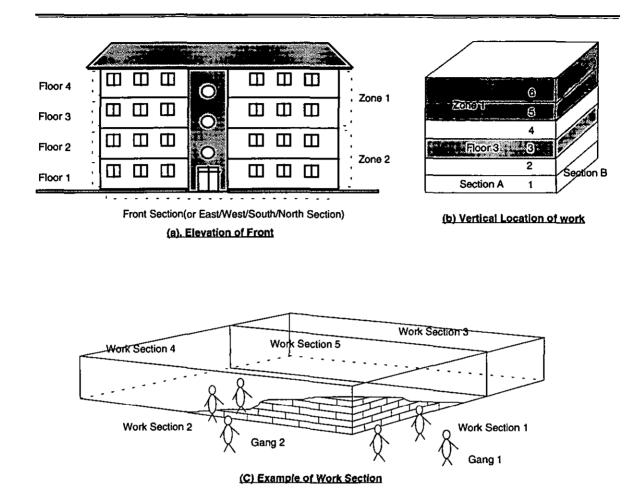


Fig 4.6 Identification of Work Section

The determination of the most suitable work section is based on two criteria which are the work sequence consideration and size of project. The key issue in the breakdown of work section is the planner's knowledge. He should determine the best manageable set of work sections within a project. He has to carry out analysis based on the heuristic knowledge bearing in mind work flow or learning curve effect, meeting with other trade requirements, etc. Thus, the determination of the WSBS is left to the planners' discretion, since it would be very complicated to standardise this process due to the uniqueness of construction

process. Defining heuristic rules for the selection of appropriate work sections may need further research in this direction.

Generally, a project can be broken-down into segments of work both horizontally and vertically. The division of work sections is performed repetitively and in such a manner that each task team can perform activity simultaneously in separate sections as shown C in Fig. 4.6. The work section might be broken-down into several levels as follows:

- Work Section: For convenience, this can be broken-down into four direction(e.g., east, south, north, west) within a single floor.
- Floor: Grouping work sections into a particular floor. A floor is aggregation of work sections
- Zone: Grouping floors into a particular Zone or it could comprise of a single building. Thus, defining Zone is depended on the size of project.
- Project : Grouping Zones into a particular project.

Fig. 4.6 shows the possible division of work sections.

C. Operation Breakdown Structure(OBS)

Building components are constructed by specialist trade teams. The work undertaken by the trade teams is referred to as the operation. The name of operation is derived from the trade name and material name. The description of this is usually described by the verb, for example, pour concrete, laying brick/block, etc. The operation is an aggregation of work items. This contains information about the nature of work, i.e., method of work, gang size, types of material used, number of tasks etc. The Operation Broken-down Structure can

be established by using the CAWS(1987) and SMM7(1988) classifications. The CAWS classification is shown in Appendix B.

4.4.3 Description of Activity Name

Activity name must be able to represent a specific feature of an activity. This may requires a full description of an activity for clarification purposes. Suppose, from the representation structure as shown in Fig.4.5, the three example activities can be identified as shown in Table 4.1.

Activity No.		Activity Description			
	Activity Name	Main Work	Extra Work	Sundry Work	AUR
Activity 1	Ex.Wall-WS1-Brick/Block	Facing-one side-Streach	Sill	DPC-Insulation-Closing-Tray	.
Activity 2	Ex.Wall-WS2-Bricl/Block	Same as above	Sunk Bond	Same as above	
Activity 3	Ex.Wall-WS3-Brick/Block	Same as above	Projecting Bond	DPC-Insulation-Closing-Tray-Holes	
etc.					

Table 4.1 Activity Description

However, if an activity name is too long as shown in Table 4.1, it is not practical for use in a scheduling package. This requires that activity names must be concise. For this reason, an activity name, say Ex.Wall-WS1-Brick/Block, may be more suitable for use with scheduling tools.

4.5 Generating Standard AUR

In the previous sections, a formalised method of defining activity was discussed. In this section, a formalised process of generating AUR is discussed.

4.5.1 Classification of Work

It is necessary to have a classification of work so that tasks which are associated with an activity can be identified, based on this work classification table. This table provides a guide-line to define the main work items, extra work items and ancillary work items in an activity. Fig.4.7 shows the work classification for the brick/block operation.

Basically, a masonry work consists of the three headings: main works, extra works and ancillary works. These are explained in more detail as follows.

- Main work: This is the major work item which requires the major proportion of time needed in completion of an activity. It is usually related with the major material type in an activity.
- Extra work items: These are additional work items along with the major work items.
- Ancillary work items: These are miscellaneous work items other than major and extra
 work items such as insulation, DPC, expansion joint, etc.. These items are usually
 associated with various material types.

Work Types	Items	Bond Types	Wall Thickness
1	1. Walls-facing and pointing Both	1. Strecher Bond	0.5 B
	2. Skin of hollow wall, one side	2. Flemish Bond	1 B
Main	3. Piers	3. English Bond	1.5 B
work	4. Curved wall		
	etc.		
	1. Sunk Band	,	
	2. Projecting Band		
Extra	3. Quoins		
work	4. Flushing and pointing		
	5. Coping, sill		
	etc.		
	1. Damp Proof Course		
	2. Insulation		
	3. Closing Cavity Wall		
Ancillary	4. Cavity Wall Insulation		
work	5. Expantion Joints		
	6. Holes for pipes, tubes, cables, etc.		
}	etc.		

Fig.4.7 Work Classification

The purpose of the work classification is for the data extraction from a data base. Also it can be used to as a check list to identify the number of tasks contained in an activity. The data structure based on the work classification defined above are shown in Fig.4.8.

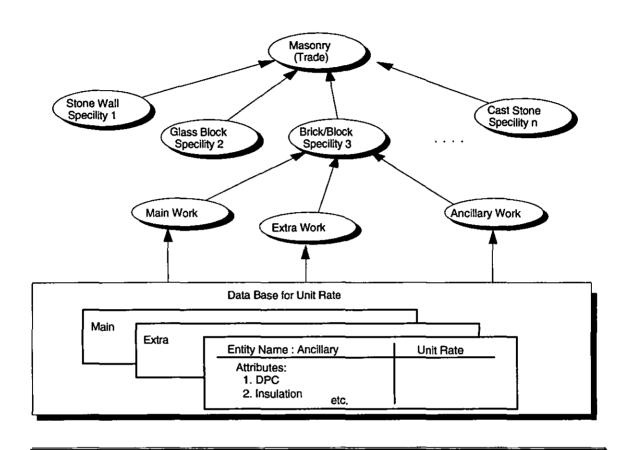


Fig. 4.8 Data Structure

4.5.2 The Process of Generating AUR

The method of identifying activity was discussed in section 4.4. Suppose, an activity is defined from the representation structure. Then, the process of generating AUR can be explained by using an example activity as shown in Fig. 4.9.

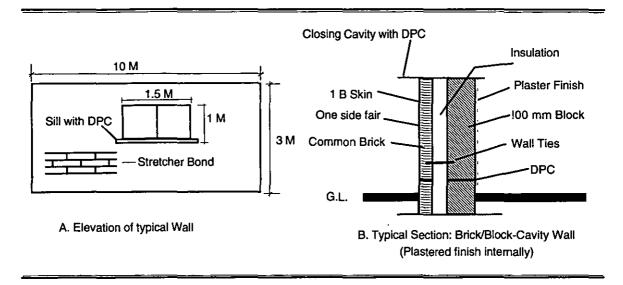


Fig. 4.9 Typical Brick/Block Wall

The process of generating AUR can be summarised as:

- 1). Identify number of tasks embedded in the activity
- 2). Take-off the quantities in each tasks
- 3). Unit rate extract on a data base
- 4). Data input(task quantity and unit rates) to the Microsoft Excel Spreadsheet program
- 5). Generate AUR

This process was implemented using Microsoft Excel. It should be noted that the AUR generated by this process is referred to as the standard AUR, since the data used in this process represent nation-wide average productivity rates. Table 4.2 shows the detailed information regarding to the various tasks in an activity. This activity work sheet contains the detailed estimation of tasks' duration/cost. Table 4.3 shows the activity summary information which contains the activity duration, cost and AUR. Table 4.4 shows an example of an adjusted activity duration/cost. This will be discussed in section 4.6.2.

GENERATING STANDARD AUR

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	1						
···-	Gang Rate(Brick)	7.06		<u>-</u>	··	-	
	Gang Rate(Block)	8.11					
					·		
	 -					 	
							<u> </u>
Labour	Labour Unit Cost	Task Labour Cost	Material Unit Cost	Task Material Cost	Equipment	Task Duration(MH)	Task Cost
(MH/M*M)	(£/MH)		_(£/M*M)_				
1.00	10.71	000.40	16.43	468.26		51.30	£830.43
1.80	12.71	362.18	10.43	408.20		51.30	1830.43
0.90	7.30	208.02	5.08_	144.78		25.65	£352.80
					Sub Total	76.95	£1,183.23
			<u> </u>			 	<u> </u>
0.75	5.30	7.94	4.09	6.14		1.13	14.08
			<u> </u>				
		<u>. </u>					
	211			10.70			040.00
0.02	0.14	3.04	0.64	13.76		0.43	£16.80
0.30	2.12	21.18	1.30	13.00		3.00	£34.18
0.12	0.85	24.15	2.74	78.09	· · · · · · · · · · · · · · · · · · ·	3.42	£102.24
0.04	0.28	8.05	0.72	20.52		1.14	£28.57
0.10	0.71	_7.06	9.93	99.30		1.00	£106.36
			Material Total	843.84	Sub Total	8.99	£288.14
		7	able 4.2 Continue	d			
1 abic 4.2 Continued							<u> </u>

4.6 The Applications of AUR

4.6.1 The Process of Project Duration and Cost Estimation

For project planning and scheduling purposes, a projects need to be broken-down into activities. In this way, the total project time/cost can be estimated by summation of each activity time/cost. It should be noted that the direct project cost, DC, is based on the direct cost only. This can be calculated by the sum of the individual direct activity costs, AC. The individual activity cost, AC, is the sum of labour cost, AL, material cost, AM, and plant cost, AP. This is shown in EQ.4.8.

$$AC_i = AL_i + AM_i + AP_i$$
(4.8)

The direct project cost, DC, is then computed as follows:

$$DC = \sum_{i=1}^{n} AC_i$$
(4.9)

where n = number of activities, $AC_i = \cos t$ of activity i(i=1,2,...,n).

The direct activity cost used here is based on the average project condition prior to the consideration of factors influence on activities. The contingency allowance for the factors impact on activity has to be added in the direct activity cost. This will discuss in the next section. The overall process to estimated project duration/cost is summarised in the Fig. 4.10.

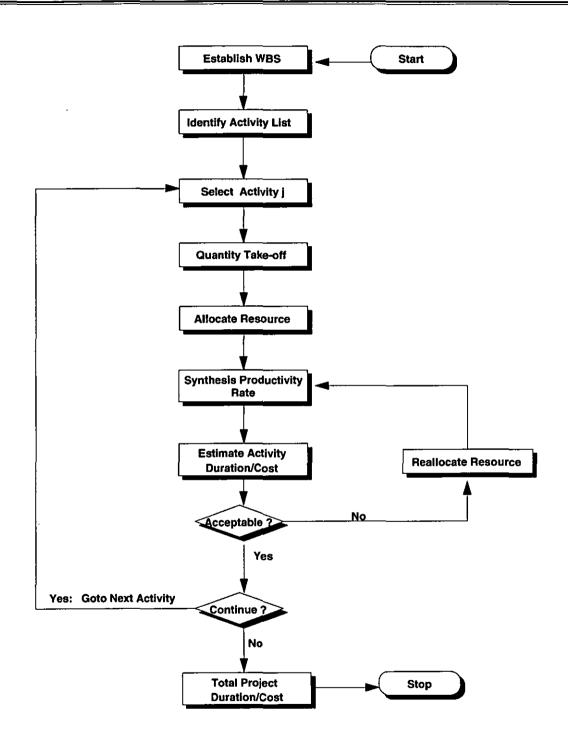


Fig. 4.10 Overview of Project Estimation Process

An estimation of activity duration/cost is usually based on the given resource allocation with a specified work method for that activity. If, an activity duration/cost does not satisfy the planner's requirement/target, then he has to reallocated the resources input for an activity. Fig. 4.10 shows this process.

4.6.2 Estimation of Adjusted Activity Duration/Cost

Once a standard AUR is defined by the proposed method in section 4.5.2, it requires adjustment in order to take account of the various factors. Suppose, the standard AUR is adjusted using a suitable adjustment mechanism(Chapter 5 will address the adjustment mechanism), then the Adjusted AUR(AAUR) can be used to modify the initial estimated activity time and cost. The process of adjustment of initial estimate as shown in Table 4.4. The following explains the adjusted activity duration/cost estimation.

A. Adjusted Activity duration

$$AD = AAUR \times AQ$$
(4.10)

where AD is the adjusted activity duration, AAUR is the adjusted AUR, AQ is the activity quantity.

B. Direct Activity Cost

As mentioned in the previous section, the direct activity cost is the sum of 1) Labour cost, 2) Material Cost and 3) plant cost. It is assumed that the plant is not used for this example activity. Thus, only the labour cost and material cost are considered.

1) Labour Cost

Labour Cost of Activity =
$$AAUR \times AQ \times Gang$$
 Rate(4.11) where gang rate is shown in Table 4.2.

2) Material Cost of activity

Material cost is assumed not affected by the factors. Thus, material cost is same as the initial estimate.

Material Cost of Activity =
$$\sum_{i=1}^{n} (Task_i Material Cost)_i$$
(4.12)

4.6.3 Classification of AUR

The concept of AUR can be explained by using a hypothetical graph as shown in Fig. 4.11. Form this, AUR can be classified into four heading which are:

- Ideal AUR
- Actual AUR
- Standard AUR
- Adjusted AUR

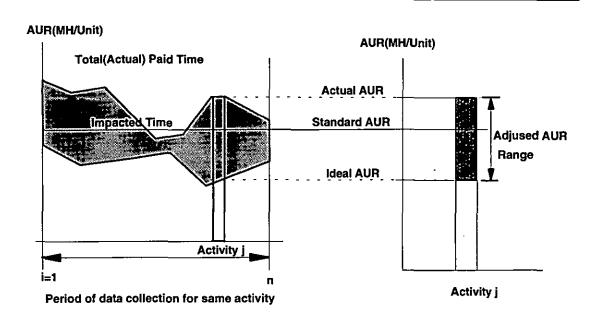


Fig. 4.11 The Concept of AUR

A. Ideal AUR

Ideal time means the time spent on an activity under the best working conditions with a well motivated and skilled work force. Often this refers to the shortest possible time to finish a specified quantity of work for an activity when we are considering MH/Unit productivity. If AUR is based on the ideal working conditions, it is referred to as the ideal AUR. Theoretically, an ideal AUR can be measured from actual AUR discounting impacted productivity once a project is completed. However it is very difficult to define the ideal AUR due to the difficulty of measuring the impacted time caused by the various factors interaction. Furthermore, collecting and keeping this data for each project is not feasible in reality. For this reason the standard AUR is used as a standard for determining the most likely AUR under a given set of factors influence on an activity.

B. Actual AUR

The duration of an activity is the paid time to complete the specified volume of work for an activity including all other necessary work. The other necessary work implies preparation work, supporting work, and any breaks required whilst performing an activity. If an AUR is defined in this way, it is referred to as the actual AUR.

C. Standard AUR

The standard AUR is the cumulative average of actual AUR. In this respect, the standard AUR can be determined by:

Standard
$$AUR = \frac{\sum_{i=1}^{n} AUR_i}{n}$$
(4.13)

Most existing estimating books are based on the average productivity which reflects a nation-wide average. Thus, if the AUR is synthesised from these sources, then it is referred to the Standard AUR(SAUR). This value is assumed to be average unit rate of an activity under average project conditions. This value will be used as the standard value for developing an adjustment mechanism in chapter 5.

D. Adjusted AUR

For the factor analysis, the adjustment can be made by applying +/- x % to the SAUR to allow for the factors' influence, since the actual AUR may vary from the SAUR. If the SAUR is adjusted by some sort of mechanism, this value refers to the Adjusted AUR(AAUR). These values are needed by a site manager to set up target for project control purposes. Furthermore, they are also required by the planner to predict the most likely activity duration and cost under specified project conditions.

E. Application of AUR

In summary, the possible applications of AUR in construction management can be illustrated in Fig. 4.12.

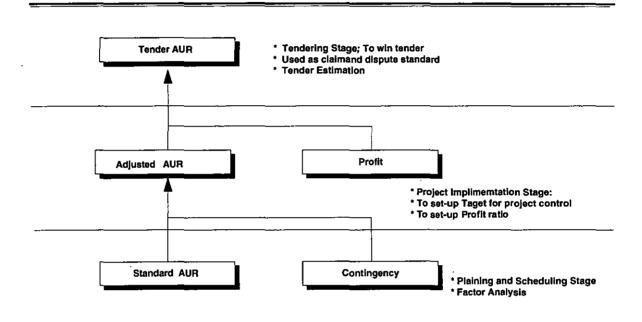


Fig.4.12 Application of AUR in Construction Management

4.7 Summary

In this chapter, the method of identifying an activity and the method of generating Standard AUR are presented.

A. Method of Identifying Activity

The representation structure for identifying an activity is presented by combining the three hierarchical structures. Based on this frame work, construction activities can be identified. This process can be implemented by a number of expert system shells and KBS development tools such as ARTTM, KEETM, Knowledge CraftTM, etc..

B. The Method of Generating Standard AUR(SAUR)

The method of generating the SAUR is presented in this chapter. This requires a clear definition of activity, since this provides the number of tasks associated with an activity. From this information, the SAUR can be synthesised from existing estimation sources. However, the SAUR should often be adjusted in order to take account the special conditions surrounding an activity operation process. This task requires considerable personal skill and expertise. Many problems arising out of the adjustment process are usually solved in an intuitive way based on the project engineer's experiential knowledge. Therefore it requires a good adjustment system which can handle this heuristic knowledge in a formalised and systematic way. Designing such a system is the topic of the next chapter.

Chapter 5: Formulation of AUR Adjustment Process

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5.1 Introduction

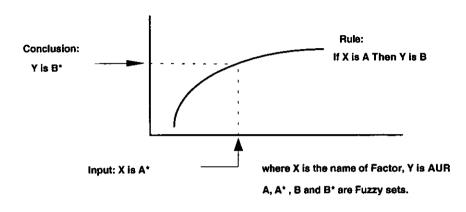
In the previous chapter, the method of generating the Standard AUR(SAUR) was presented. However, SAUR should be adjusted in order to take account the various factors faced in a project. In this chapter, the method of adjusting SAUR is proposed by utilising fuzzy set theory and fuzzy logic as presented in chapter 3. The primary purpose of the method proposed herein is to rationally structure and systematise the AUR adjustment process. The adjustment process is summarised in the form of a fuzzy rule based system named 'Fuzzy Activity Unite Rate Analyser(FAURA)'. A computer program has been written to implement FAURA by using Turbo Prolog.

5.2 The Concept of AUR Adjustment

5.2.1 The Fuzzy Concept

Zadeh introduced the theory of approximate reasoning(Zadeh 1975c). The theory of approximate reasoning is based on fuzzy logic(Zadeh 1973, Zadeh 1975b, Zadeh 1976, Zadeh 1978, Mizumoto et al. 1979, Zadeh 1983, Dubois and Prade 1991). This is the generalised modus ponens which is the extension of the traditional modus ponens inference method. The modus ponens is working in such way that 'if X is A then Y is B' and 'X is A' holds, implies that 'Y is B' holds(Bouchen-Meunier 1992). In the case of fuzzy logic, a generalised modus ponens, takes into account both the rule 'if X is A then Y is B' and input 'X is A*', where A* is identical to A or not, yielding a conclusion 'Y is B*', where B* can be different from B. Obviously, if A* is too different from A, then the

inference result can not provide a meaningful result which is B*. We shell denote this as the fuzzy inference.



A. Fuzzy Inference Concept

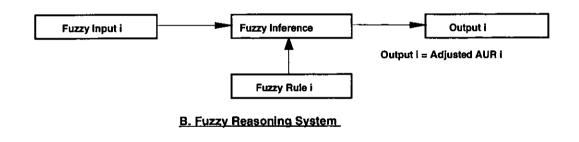


Fig. 5.1 The Fuzzy Inference Concept

A typical fuzzy inference example given by Mizumoto and Zimmermann(1982) is:

Premise(input):	This tomato is very red	
Implication(rule):	If a tomato is <i>red</i> Then the tomato is <i>ripe</i>	(5.1)
Conclusion(output):	This tomato is very ripe	

The interpretation of this example is that knowledge that increase in "redness" indicates an increase in "ripeness". This is the fuzzy concept to deduce unknown conclusions from given inputs and rules. It may be possible to apply the same concept as shown in the tomato example in EQ.5.1 to the AUR adjustment. The concept to deduce the AUR is explained in chapter 3. Fig. 5.1. shows this concept.

To explain this concept in more detail, consider an activity j influenced by several factors. Consequently, AURj will vary according to the those factor's present with certain degree. However, the problem is that the causal relationship between the factors and AUR is not known precisely in many cases. In such uncertain or vague causal relationship, human experts tend to use linguistic terms to describe the causal relationships. It is appropriate, therefore, to use the fuzzy production rule(fuzzy rule) format to capture the uncertainties contained in the casual relationship as follows:

Rule
$$i: If F_i$$
 is A_i Then AUR_j is B_i (5.2)

where Fi is the factor i name,

AUR; is the name of unit rate of activity j,

Ai and Bi are fuzzy sets which are the linguistic values.

From this perspective, the AUR deduction concept can be stated in the form of fuzzy inference as follows:

Input:
$$F_i$$
 is A_i^*
Rule: If F_i is A_i Then AUR_j is B_i (5.3)

Output: AUR_i is B_i*

where A_i^* is input fuzzy set which is the measure of the degree of Factor $i(F_i)$ and B_i^* is deduced AUR.

It is unrealistic to believe that experts know everything about a domain under consideration. Thus, if experts provide some of the basic rules regarding the causal relationship, then the rest of the unknown causal relationships have to be provided using the some sort of deduction mechanism or educated guess. Therefore, an efficient reasoning system has to be designed, which can satisfy this requirement. The following section discusses the overall adjustment process to deduce an adjusted AUR.

5.2.2 The Overall Adjustment Process

The previous section describes the application of the fuzzy inference concept for the determination of AUR. This section describes the concept of the overall AUR adjustment process. Fig. 5.2 shows this process. This process consists of three parts which are: (1) Input, (2) inference mechanism, and (3) output. The following describes these briefly.

A. Input

To explain the overall AUR adjustment process, assume that an activity j from a work package has been selected for the analysis. The next step is then to identify the list of factors for this activity. These factors can be identified from drawings, site visit, past experience, time of construction, and so on. Let assume that a user identify n factors for activity j. Let Factor i(Fi, i=1,2....,n) denote them. Then, the Degree of Factor(DF) has to be measured for each of factors according to the pre-defined input measurement scale.

Section 5.3.2 discusses the user input format. Suppose that, a user provides the values of DF for each factor by using the user input format, then these values can be used as inputs for the fuzzy inference.

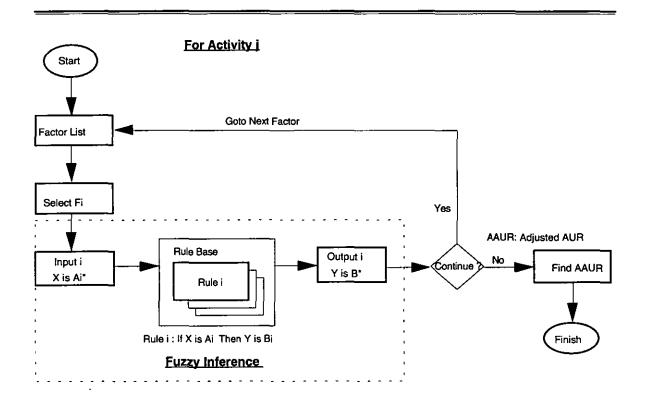


Fig. 5.2 Overall AUR Adjustment Process

B. Inference mechanism

The next task is to determine how much activity j is susceptible to the identified(or observed) Fi. This process requires an appropriate inference method to deduce the AUR under the observed Fi. The method required to perform this process is based on the compatibility measurement(Nafarieh 1991). Using this method, the deduction process to generate AUR can be performed. This deduction process is discussed in the section 5.3.

If we assume that there are adjustment rules and an appropriate inference method available, then it would be possible to calculate AUR factor by factor in turn.

C. Output

At the end of this process, there will be n outputs, as each factor results in one particular output. Thus, a method of summing up all outputs is needed. The output interpretation will be discussed in section 5.3.4. This completes one cycle of the AURj adjustment process for activity j. The same procedure can be repeated until all the activities in the work package have been considered. Once the AURj has been defined for each activity, it is used to calculate the most likely activity duration/cost, which will be used as input for any scheduling tools for project planning and control purposes.

5.3 Formulation of AUR Adjustment Process

In the previous section, a number of tasks are identified to formulate the AUR adjustment process which are:

- Rule Base
- Fuzzy Inference
- User Input
- Fuzzy Output

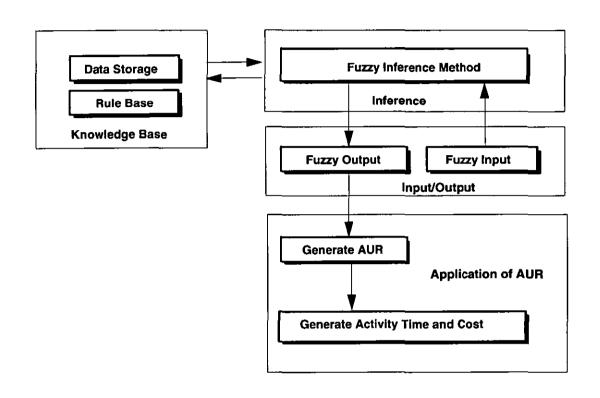


Fig. 5.3 Structure of FAURA

These are the components of a fuzzy rule based system named as 'Fuzzy Activity Unit Rate Analyser(FAURA)'. The structure of FAURA is shown in Fig.5.3. To yield a sound adjusted AUR, these components must be formulated in an appropriate manner. The following sections discusses these components in more detail.

5.3.1 Rule Base

5.3.1.1. Fuzzy Propositions

A causal relationship is knowledge about cause and consequences. Usually, knowledge about a domain is expressed as a proposition. The fuzzy rule is used to capture and rationalise one's perception about uncertain causal relations(refer section 3.3 in chapter 3). For the AUR adjustment, it is necessary to examine the three domains which are: (1) Degree of Factor(DF), (2) Degree of Impact(DI), and (3) AUR, since these domains are interrelated to each other. In order to examine the three domains, consider an internal brick wall activity under bad weather conditions. We may want to know what will be the unit rate of this internal wall activity as a consequence of the bad weather. In these circumstances, the Degree of Impact(DI) on the internal brick wall activity may not be significant to the degree of factor(bad weather) since an internal brick wall activity is not susceptible to the weather conditions. Thus AURj can be estimated as normal(or average) under bad weather conditions.

On the other hand, for an external wall activity without weather protection under the same factor with the same degree(bad weather conditions), the DI may be very significant since the nature of the activity is susceptible to the DF(bad weather). In these circumstances, the degree of Fi will dictate the DI. Thus, AURj can be estimated as high as a consequence of bad weather conditions.

The example propositions of the three domains for a specified activity j as explained above can be expressed as:

P1 for DF: Weather condition in Loughborough is **Bad** (or X is A)

P2 for DI: Impact on Activity j is Significant in a negative way (or Z is C)

P3 for AUR: AUR j is *High* (or Y is B)(5.4)

These are the fuzzy propositions which state the knowledge about domains where the values of variables are linguistic terms instead of precise numerical terms. The assignment of linguistic term in a proposition can be done in two ways: (1) by functions(or models), or (2) by expert's best judgmental knowledge available at that time. In this study, the assignment of linguistic term is based on the expert knowledge.

5.3.1.2. Hypothetical Syllogism

The hypothetical syllogism as stated in EQ. 5.5 is useful to structure the rule. Suppose we have the three propositions which are P1, P2, and P3. The hypothetical syllogism states(Frost 1987):

which are interpreted as 'P1 implies P2' and 'P2 implies P3', where P1, P2 and P3 are propositions. From EQ.5.5, we can infer that P1 \rightarrow P3 is true in all cases in which P1 \rightarrow P2

and P2 \rightarrow P3 are true. Therefore, we can concluded that P1 \rightarrow P3 is a logical consequence of P1 \rightarrow P2 and P2 \rightarrow P3. However, when we are dealing with some uncertainty associated with chaining rules, the consistency of the consequences has to be considered. For example, if there is uncertainty in the relationship between the given two propositions as shown in EQ. 5.5, the degree of certainty $c(P1\rightarrow P3)$ is a function of $c(P1\rightarrow P2)$ and $c(P2\rightarrow P3)$. More details in this regard can be found in Dubois and Prade(1991). In this study, the uncertainty associated with chaining relationship is not considered, since the logical consequence in all propositions is assumed to be true. The advantages of using the hypothetical syllogism are twofold. Firstly, it can simplify the computational process to deduce a conclusion in the reasoning process. Secondly, it makes it possible to significantly reduce the number of rules.

5.3.1.3 Structuring Fuzzy Rule Base

Suppose that one may establish all necessary propositions regarding the DF, DI and AUR for a specified activity j. From these propositions, it is possible to structure the required rules for the reasoning system under consideration. This can be structured by using the hypothetical syllogism as explained the previous section. This is illustrated below:

Rule 1: If Fi is Ai Then DI of activity j is Ci

E.g.: If Weather conditions in Loughborough is *Bad* Then DI of activity j is

Significant(-)

Rule 2: If DI of activity j is Ci Then AURj is Bi(5.7)

E.g.: If DI of activity j is Significant(-) Then AUR; is High

From EQ.5.6 and EQ.5.7, it is possible to deduce:

Rule 3: If Fi is Ai Then AURj is Bi

.....(5.8)

E.g.: If Weather Condition is **Bad** Then AUR; is **High**

where Fi is the name of the factor(such as design factor, site, weather, management control, etc.), AUR j is the unit rate of Activity j, Ai and Bi are fuzzy sets such as *high*, *low*, *good*, *bad*, *average*, *very good*, *quite*(*pretty*) *bad*, *more or less high*, *etc.*. EQ.5.8 is the rule format used in this study. It is important to note that all of the linguistic estimations(value) used in these rules should be from the knowledge gained in the years of practical site experience from experts such as site managers, planners, estimators, etc..

A rule base is the collection of rules as shown in EQ. 5.8 in an organised way. For example, an example of rules about a causal relationship, between weather conditions and AUR can be established as:

Rule 1: If Weather is Bad, Then AUR j is High

Rule 2: If Weather is Average, Then AUR j is Medium(Average)

Rule 3: If Weather is Good, Then AUR j is Low

... etc.

In FAURA, the above rules are represented by the following clause structure in Turbo Prolog(Shafer 1987):

Rule 1: rule(weather, bad, "weah.dat").

Rule 2: rule(weather, average, "weam.dat").

Rule 3: rule(weather, good, "weal.dat").(5.9)

or in general,

rule(Fact_name, Ai, "file name")(5.10)

where 'rule' is a keyword which represents the name of the clause. The first argument in the clause, 'Fact_name', is a factor name such as crew factor, weather, site conditions, etc. The second argument 'Ai' is the linguistic value of DF in the premise of rule(Fi is Ai) which is the first part of rule. The third argument 'file name' is a fuzzy set(Bi) of AURj in the consequent part of rule. The fuzzy set Bi is defined by the 'Curve.C' computer program written in this study to implement Zadeh's standard membership functions(refer next section). Once all fuzzy data sets are generated by the computer program, they must be saved under a specified sub directory as data storage.

5.3.1.4 Fuzzy Set in Rule

So far, we have not discussed how to interpret linguistic terms into fuzzy set used in the rule. This section discusses the method of generating the fuzzy sets used in the rule base.

A. Standard Membership Functions

The linguistic terms used in the premise of rules(Fi is Ai) are the linguistic estimation of Degree of Factor(DF). These terms are used to describe the degree of factor as a

scale(refer section 5.3.2). The primary terms are only used in the premise of rule(EQ.5.8). The primary terms are atomic terms such as *high*, *low*, *medium*, *good*, *bad*, *etc*. without any modifiers(hedges) such as *very*, *more or less*, *very very*, *quite*, *etc*.

However, the linguistic terms used in the consequent part of a rule(AUR j is Bi) as shown in EQ.5.8 need to be defined. These linguistic values are then interpreted into fuzzy sets. In this study, Zadeh's standard membership functions(Zadeh 1972,1975a) are used to interpret the linguistic terms used in the consequent part of rule. In Zadeh's paper(Zadeh 1972,1975a), the two standard membership functions which are called 'S' and 'PI' functions are frequently used to interpret fuzzy set into fuzzy data set(fuzzy number). These are non linear functions. It appears that these membership functions convey a more appropriate interpretation of a fuzzy set of AUR than a linear membership function such as Triangular or Trapezoidal membership function(Kaufmann and Gupta 1988). This is due to the fact that the membership function of AUR is more likely to have a non leaver shape. The S-function, the mirror image of S-function and PI-function are used to generate a *Medium*, *High* and *Low* fuzzy set of AURj respectively. These are shown as follows.

i) π -function: For Medium

$$\pi(u;\beta,\gamma) = s(u;\gamma-\beta,\gamma-\frac{\beta}{2},\gamma); \quad \text{for } u \leq \gamma$$

$$= 1-s(u;\gamma,\gamma+\frac{\beta}{2},\gamma+\beta); \quad \text{for } u \geq \gamma$$
(5.11)

ii) S-function: For High

$$S(u; \alpha, \beta, \gamma) = 0 for u \le \alpha$$

$$= 2\left(\frac{u - \gamma}{\gamma - \alpha}\right)^{2} for \alpha \le u \le \beta$$

$$= 1 - 2\left(\frac{u - \gamma}{\gamma - \alpha}\right)^{2} for \beta \le u \le \gamma(5.12)$$

$$= 1 for u \ge \gamma$$

iii) For Low:

$$S(u; \alpha, \beta, \gamma) = 1 \qquad \text{for } u \le \alpha$$

$$= 1 - 2(\frac{u - \gamma}{\gamma - \alpha})^2 \quad \text{for } \alpha \le u \le \beta$$

$$= 2(\frac{u - \gamma}{\gamma - \alpha})^2 \quad \text{for } \beta \le u \le \gamma \qquad \dots (5.13)$$

$$= 0 \qquad \text{for } u \ge \gamma$$

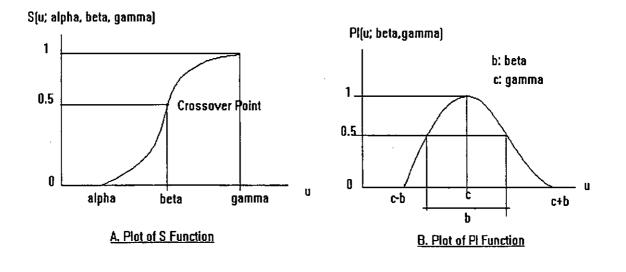


Fig. 5.4 S and PI Function

In EQ.5.12 and 5.13, the parameter β , $\beta = \alpha + \gamma / 2$, is the crossover point. In EQ. 5.11, β is the bandwidth, that is, the separation between the crossover point of π , while γ is the point at which π is unity(Zadeh 1972). Fig.5.4 shows these membership functions in more detail.

A computer program, 'Curve.C' has been written in this study to calculate these standard membership functions, using the Turbo C language. Appendix D shows the list of the computer program and example fuzzy sets.

B. Example Fuzzy Sets

To explain the use of the standard membership functions to generate fuzzy sets, consider the variability of unit rate of activity j(AURj) under factor i(Fi) influence. The standard(average) AUR under normal Fi condition is found to be 3.5 MH/M² from existing estimating sources. Suppose, an expert estimates AURj as *High* under Bad Fi influence, *Low* for good Fi influence and *Medium* for normal Fi condition.

Then the next task is to define the ranges for the fuzzy sets in terms of low limit(α), upper limit(γ) and centre point(crossover point)(β) for each fuzzy set. Determination of these values has to rely on expert subjective judgement. The scale of the range is dependent on the degree of impact. For example, if Fi has a little impact on activity j, then the corresponding scale of range will be narrow and vice versa. Let assume that an expert provides the required information as shown in Fig.(), then it is possible to generate fuzzy set by using the standard membership functions.

AUR: 1.5 2.5 3.0 4.75 3.5 6.0 Medium High Range Low range alpha beta gamma gamma For High: alpha

beta

For Activity i under Fi influence

Fig. 5.5 Ranges for Fuzzy Sets

In order to use the Curve.C computer program to generate fuzzy set data, it requires to input α , β and γ values as defined in the Fig. 5.5. Fig. 5.6 shows the three fuzzy sets generated by the Curve .C computer program based on the given information as shown in Fig. 5.5.

Table 5.1 shows the fuzzy set data as shown in Fig. 5.6.

Linguistic Terms	α	β	γ	Fuzzy Set Data
High	3.5	4.75	6.0	0/3.5, 0.09/4.0, 0.31/4.5, 0.69/5, 0.91/5.5, 1/6
Medium		0.5	3.5	0/3, 0.31/3.25, 1/3.5, 0.31/3.75, 0/4
Low	1.5	2.5	3.5	1/1.5, 0.89/2, 0.5/2.5, 0.11/3, 0/3.5

Table 5.1 Example Fuzzy Sets

All fuzzy sets used in the rule base(refer section 6.2 in chapter 6) is generated by the same process as shown in this section.

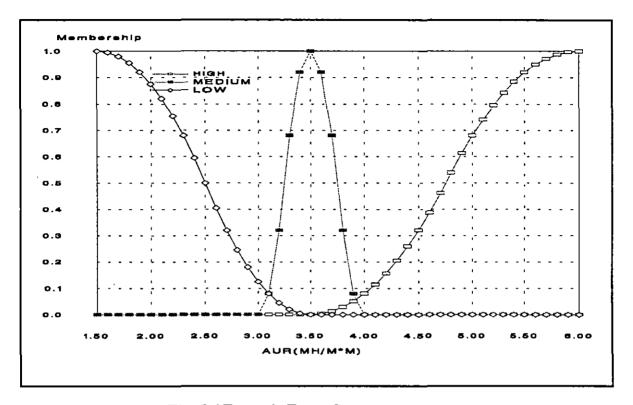


Fig. 5.6 Example Fuzzy Sets

5.3.2 User Input

The fuzzy input means providing additional information required by the inference mechanism to deduce conclusion. More specifically, a user should supply 'Fi is A*' as shown in EQ.5.3 in section 5.1.1 as input in order to deduce a conclusion which is 'AURj is B*'. The A* is a linguistic estimation of a particular factor i(Fi). The measurement of degree(state) of factor(DF) by using linguistic terms based on a pre-defined input term set, such as *good*, *very good*, *bad*, *more or less bad*, *etc*.. The collection of possible linguistic terms(linguistic value) to characterise an object(linguistic variable) is referred to

as the term set. The term-set is composite terms which are composed of primary term and a hedge(modifier). The primary term is an atomic term to represent the meaning of a variable without hedges. The hedges serve the function of generating a larger set of values for a linguistic variable from a small collection of primary terms(Zadeh 1973). For example, consider a composite term, say very good, in this case, good is the primary term and very is the hedge. Thus, the input term set is considered as an artificial language to convey the meaning of natural language expressed by the user so that the system can understand the terms. In theoretically, the number of elements in a term set may be infinite. However, practically, only a small number of terms may be needed as input values for a particular factor. There are several reasons for this.

Firstly, it is almost impossible to measure the qualitative factors in a precise scale. This is due to the non-existence of standard to measure them.

Secondly, it is due to the limitation of fuzzy set theory to quantify all sorts of linguistic terms used by user(people). For this reason, the two types of hedges(modifiers) which are **Very** and **More or Less** family are used in this study. More details relating to hedges are discussed in section 5.3.3.

Finally, another consideration when structuring a term set is the sensitivity of expected output from a given input term set. More specifically, the inference result should reflect a sensible outcome which is not drastically or little effect on the outcome by changing the input values.

Therefore, determination of an appropriate number of linguistic terms can only be judged via an experiment by sensitivity analysis. Following a trial and error approach, one can

define a more sensible number of linguistic terms for the reasoning system under consideration(Section 6.4 in chapter 6 discusses this problem).

With this view, the possible input term set is shown in Fig.5.7. It is important to note that this term set is not the uniform standard, rather this is to show an example for structuring input term set. The number of terms in the term set can be increased or decreased depending on the system requirement.

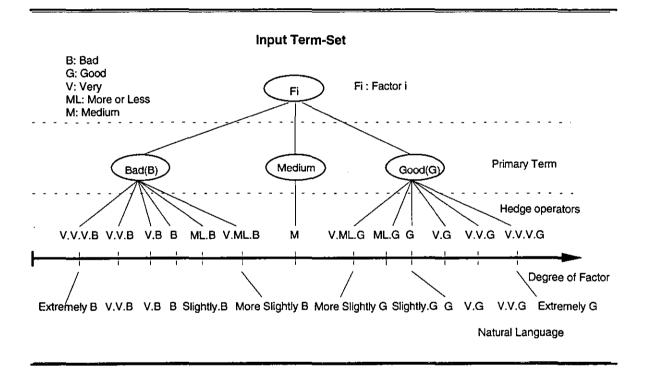


Fig. 5.7 Input Term Set

In this way, it allows uncertainties embodied in the factor measurement, since they deal with a range rather than a single numerical value. The linguistic estimation of DF is based on the assessor's subjective judgement, their knowledge and information available at that time.

5.3.3 Fuzzy Inference

In this section, the fuzzy inference used in this study is presented.

5.3.3.1 Background

There have been extensive studies in relation to the fuzzy inference method in fuzzy logic applications, since Zadeh introduced the first fuzzy inference in his seminal article(Zadeh 1973). The fuzzy inference is often called max-min operation to deduce a conclusion Y is B* from implication(rule) and input A* as the following equations(Zadeh 1975a).

$$B^* = A^* \circ R$$
(5.14)

where • is max-min composition operator, and R is a fuzzy relation for translation of a rule. R is defined by:

$$\mu_{R}(u,v) = \min[1,1-\mu_{A}(u)+\mu_{B}(v)]$$
 (5.15)

Therefore, B* is obtained by the following max-min composition:

$$\mu_{B}(v) = \max_{u} \left[\min_{v} \left\{ \mu_{A}(u), \ \mu_{R}(u,v) \right\} \right]$$
.....(5.16)

This process is the typical fuzzy inference procedure proposed by Zadeh. However, the original compositional rule of inference does not produce an exact solution for B* in some cases(Mizumoto et al. 1979, Chang 1991, Nafarieh 1991). A number of papers have

addressed the theoretical investigation to improve Zadeh's compositional rule of inference. These efforts may be classified into two distinct approaches which are: (1) the implication approach; and (2) the compatibility measurement approach.

The implication approach tries to formulate(or modify) an alternative implication operator as shown in EQ.5.15 by changing the translation of the rule into the fuzzy relation R. There exist over 10 different ways of defining fuzzy implications(Nafarieh 1988,1991, Dubios and Prade 1991, Bouchon-Meunier 1992) to improve the fuzzy inference.

Besides changing EQ.5.15, the compatibility measurement approaches have been proposed(Nafarieh 1988,1991, Dubios and Prade 1991, Bouchon-Meunier 1992). The concept of compatibility measurement is to measure the difference(refers to the compatibility) between the input fuzzy set(A*) and the premise of rule fuzzy set(A) so that this difference can be applied to deduce Y is B*(refer EQ.5.3). This approach is adopted in this study for the inference mechanism, particularly, the method proposed by the Nafarieh et al.(1991). The following section explains the reasons for using their method.

5.3.3.2 Selection of Inference Method

The selection of an appropriate inference method is dependent on the nature of the rules and types of fuzzy application under consideration. Dubios and Prade(1991) explain the two types of rules as follows:

- Truth-qualifying rules: when A and B are fuzzy sets then "if X is A then Y is B" actually means " the more X is A, the more Y is B". The tomato example(EQ.5.1) used in section 5.2.1 belongs to this type of rule.
- Uncertainty-qualifying rules: there are situations when a fuzzy rule actually means
 "the more X∈A, the more confident one is that Y∈B". A simple example for this
 type of rule is "the younger an individual, the more certain he/she is to be single".

In this study, the truth-qualifying rule is used. It is important to note that the selection of an inference strategy is dependent on the meaning of a rule, rather than an algebraic grounds. Hence, it is important to find which method best suited for a system in question. In this study, a simplified form of the compatibility measurement method proposed by Nafarieh(1991) is used. There are several reasons for this as follows:

- This approach is convenient for implementation by computer.
- Authors claim that their method is superior to the various other methods in terms of accuracy of inference results.
- The computational process to deduce a result is simple.

It will be seen that, this method produced an exact result as suggested by Mizumoto et al(1979) which satisfies our need "the more X is A, the more Y is B". The following section explains the inference process used in this study using the compatibility measurement method.

5.3.3.3 The Compatibility Measurement

Mizumoto et al.(1979) suggested that if the input fuzzy sets, A^* , are expressed as the hedges(modifiers), then the conclusions(output B^*) from the fuzzy inference should match with some intuitive conclusions as shown in Table 5.2. Table 5.2 shows the intuitive relations between input(A^*) and conclusion(B^*) in conjunction with a rule i such as 'If X is A Then Y is B'.

Modifier(hedges)	Input(A*)	Conclusion(B*)
Same(modus ponens)	X is A	Y is B
Very Family	X is very A	Y is very B
More or Less Family	X is more or less A	Y is more or less B
Not	X is not A	Y is unknown

Table 5.2 Some Intuitive Relations

These are the expected consequences from the application of fuzzy logic in a fuzzy rule based system which should satisfy the intuitive relations as shown in Table 5.2. Nafarieh et al.(1991) proposed the compatibility measurement method to yield the same results as shown in Table 5.2. In order to calculate the compatibility denote as, N, the following equations are given by them.

$$\int_{0}^{1} \mu_{M}(x)dx = \int_{0}^{1} [\mu_{ture}(x)]^{N} dx = f[comp(A^{\bullet}, A)] \qquad(5.17)$$

where

where A* is the input fuzzy set and A is a fuzzy set in the premise of rule. Let $\mu_{ture}(x) = x$ in EQ.5.17. Thus, after integration the left side in EQ. 5.17, will be 1/(N+1). Therefore, the only unknown variable is $comp(A^*,A)$. Hence, if we know the value of $comp(A^*,A)$, then it is possible to calculate the N value which is the measure of compatibility. The $comp(A^*,A)$ is defined by the following equation:

$$comp(A*A) = \frac{|A*\cap A|}{|A*\cup A|} \qquad (5.21)$$

where A^* is an input, A is a premise of rule, and \cap , \cup and $|\cdot|$ denote intersection, union and area under the fuzzy set respectively. More details regarding the compatibility measurement method and computational process are shown in Appendix C.

5.3.3.4 Simplified Method

According to the compatibility measurement method proposed by Nafareih(1991), the input fuzzy set A* and fuzzy set A in the premise of rule are compared to define the N value by using the serious of equations as shown in the previous section. However, this process can also be implemented by using the hedge operator defined by Zadeh(Zadeh

1972, 1975a). The core concept of using the hedge operators in this study is that if an input, A*, is represented by the modifiers(hedges) such as very A, very very A, more or less A, not A, etc., then it is possible to quantify its meaning by using the hedge operators. After comparison between input, A*, and premise of rule A, then it is possible to define the compatibility measurement, the N value, by using the hedge operators. Once, the N value is defined, then it is applied to the power of B in order to deduce the B* as suggested by the Nafarieh(1991)(refer EQ.5.28).

It is important to notice that there are limitations of using hedges for the input linguistic terms. The type 1 hedges are used in this study as follows(Zadeh 1972):

- Expansive hedges such as very, very very, strongly etc.
- Restrictive hedges such as more or less, somewhat, similar, etc.

The following show the hedge operators used in this study.

Case 1: very hedge: if an input linguistic term, A*, is expressed as 'very A' where A is a primary term used in the premise of rule, then the meaning of the input, A*, is given by (Zadeh 1972):

Input
$$A^* = Con(A) = very A = A^2$$
(5.22)
where $Con(A)$ is concentration operation.

or in general,

$$M(\text{very....very A}) = A^{2n}$$
(5.23)

where n is the number of very in the term very....very A.

Case 2: more or less:

Input
$$A^* = Dil(A) = more \text{ or less } A = A^{0.5}$$
(5.24) where $Dil(A)$ is dilation operation.

or in general,

M(very ... very (more or less A)) =
$$(A^{0.5})^n$$
(5.26)
where n is the number of very in the term very...very(more or less A).

The hedges used in the input linguistic term, A*, are not the natural languages, i.e., these are artificial languages acting as operators. This process provides the semantic rule to define the N value. This is shown in EQ.5.27 as:

$$A^* = A^N \text{ with,}$$

$$\mu_{A} : (u) = (\mu_A(u))^N, \quad N > 0 \qquad ... (5.27)$$

where A^* is the input fuzzy set, A is the fuzzy set in the premise of rule, N is the compatibility measurement. For example, if an input value, A^* , = Very A for Fi, and A is the premise of rule, then the N value will be 2 according to the EQ.5.22. When the N value has been defined from comparison between A^* and A, this value is applied to the power of B. This is given by the following equation(Nafarieh 1991):

$$B^* = B^N$$
 with,
 $\mu_{B^*}(\nu) = [\mu_B(\nu)]^N$ (5.28)

where B* is the deduced conclusion, B is the fuzzy set in the consequent part of the rule.

A simple example for this is as follows.

Let N = 2

Fuzzy set B =
$$0/4$$
, $0.2/4.5$, $0.5/5$, $0.7/5.5$, $0.8/6$, $0.9/6.5$, $1/7$(5.29)
Then B* = B² = $0/4$, $0.04/4.5$, $0.25/5$, $0.49/5.5$, $0.64/6$, $0.81/6.5$, $1/7$.

In this study, only two types of hedge are used. However, in future, it will be desirable to expand to the other types of hedges such as much, slightly, sort of, etc..

5.3.4 Fuzzy Output

5.3.4.1 Fuzzy Output Interpretation

As a result of inference, the possible outputs(B*) might have the following forms.

For F1:

AUR; is very very high

For F2:

AUR; is more or less low

For F3:

AUR; is very low

ETC...

or in general:

For F_i : Y_i is B_i^* (5.30)

where Y_i is the name of the unit rate of an activity j and B_i^* is an output fuzzy set representing the value of AUR.

Thus, if we have n factors, then there will be n outputs as shown in Fig. 5.8.

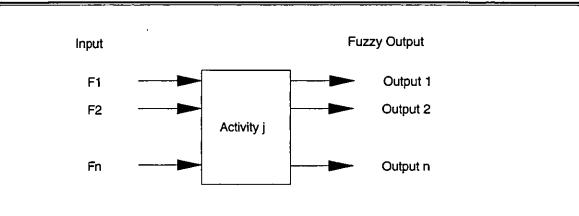


Fig. 5.8 One to One Relationship

However, we need a single numerical counterpart for the each output fuzzy set so that activity duration/cost can be calculated based on this value. Thus there is a need to have an interpretation method for the output fuzzy sets. Zadeh introduced the following Fuzzy Mean(FM) formula(Zadeh 1975c) for this purposes as:

$$FM(B_{i}^{*}) = \frac{\sum_{i=1}^{n} \mu_{i} \times u_{i}}{\sum_{i=1}^{n} \mu_{i}}$$
 (5.31)

where μ_i is membership value and u_i is member(element) of a fuzzy set.

The purpose of the FM is to interpret the meaning of fuzzy set into a representative single number. For example, consider the fuzzy set B, say *high* AUR, used in EQ.5.30.

The interpretation of the fuzzy set, B, can be calculated by using EQ.5.31 as:

$$B = 24.45 \div 4.1 = 5.96 \text{ MH/M}^2$$
 (5.32)

Thus, this value is used to represent the meaning of linguistic term, high.

5.3.4.2 The Output Treatment

As shown in Fig. 5.8, all factors impact on particular activity j simultaneously. In such case, there is a need to have a method to provide an overall assessment of factors impact on a particular activity j. This requires a method summing up the individual outputs which is generated by using the EQ.5.31 in order to take into account an additional cumulative effect, since the overall impact on activity j is compounded by the factors interaction. The overall assessment of factors impact on a particular activity is represented by the Adjusted AUR(AAUR). This can be expressed by the following equation(consider 5 factors only).

$$AAUR = f(F_1, F_2,, F_5)$$

$$= (\theta_1 \times \theta_2 \times \theta_3 \times \theta_4 \times \theta_5)^{\lambda} \times S \qquad (5.33)$$

$$= (\frac{O_1}{S} \times \frac{O_2}{S} \times \frac{O_3}{S} \times \frac{O_4}{S} \times \frac{O_5}{S})^{\lambda} \times S$$

where

AAUR = Adjusted AUR,

 $F_i = Factor i(i=1,2,...,5),$

 θ_i = coefficient of Output i(i=1,2,...,5),

 λ = Overall output adjustment coefficient,

 $O_i = Output i under F_i impact(i=1,2,...,5),$

S = Standard(average) AUR for the particular activity j(Constant value).

The purpose of EQ.5.33 is to take account the multi-factor interaction on the activity j. The logic of this equation is derived form the concept of unit. More specifically, if all factors are having average condition, then the overall measure should be same as the Standard AUR(S). This means that the all θ values are equal to unity, i.e., one. EQ.5.33 represents this concept.

The purpose of the λ is to adjust the product of coefficient output values, θ , in EQ.5.33, because the result from EQ.5.33 might be too higher or lower than what we expected without λ . In EQ.5.33, the two parameters which are the output(Oi) and S are the known values. The only unknown value is the overall adjustment coefficient value, λ . In such case, we can increase or decrease the value of λ until the resulting AAUR matches with some standard. In order to establish the standard, it requires collection of large volume of data from fields, since we cannot set-up experiment to collect sufficient data. No absolute answers can be given to determine the λ value. However, in a situation where collection of data is not feasible or too expensive to collect them, then the user(decision maker) can determine the value of λ after consultation with field experts. For example, if an expert provides some idea for the AAUR under worst or best condition, then it can be used as a basis(standard) to define the value of λ .

Nevertheless, the accuracy of system output will be considerably enhanced by repeating this process until a reasonable solution is found. At current stage, it is not feasible to define the absolute λ value, since no research(historical data) regarding to this respect have found by the author. Although several studies in relation to the labour productivity

variability(Sander 1989, Horner 1990, Thomas 1994) have been published, these studies are not sufficient to determine the λ value. Since these studies are focused on the daily labour productivity variability on a specific very simple operation. Further study is needed to find the best solution for the determination of the λ .

For the temporary solution, assuming that an expert provides an AAUR value, under the worst factors combination, say 2.5 times higher than SAUR value(3.5 MH/M²) which gives 8.75 MH/M² unit rate for an activity j, even though this is rarely happen in real world. Nevertheless, this information can be used as the basis for determining the value of λ in this case. The following example explains this concept in more detail.

Case 1: All factors are worst condition. The expected consequences in this case is 8.75 MH/M².

Let

 $SAUR(S) = 3.5 MH/M^2$.

O1 under F1 with worst condition = 7.005 MH/M^2

O2 under F2 with worst condition = 5.702 MH/M^2

O3 under F3 with worst condition = 5.267 MH/M^2

O4 under F4 with worst condition = 4.397 MH/M^2

O5 under F5 with worst condition = 3.961 MH/M^2

Using EQ.5.33:

- 1) $\lambda = 0.6$ AAUR = $(6.97)^{0.6} \times 3.5 = 11.22$: Too high, hence not acceptable.
- 2) $\lambda = 0.5$ AAUR = $(6.97)^{0.5} \times 3.5 = 9.24$: Still too high, hence not acceptable.

3) $\lambda = 0.45$ AAUR = $(6.97)^{0.45} \times 3.5 = 8.4 \approx 8.75$: Acceptable. Since this value is closely match with the assumption.

Once the value of λ is determined by this process, it now possible to calculate the overall impact of changes in factors condition from worst to best condition on the activity j by using EQ.5.33. Section 6.4 in chapter 6 demonstrates the sensitivity of AAUR by changing the factors condition from the worst condition to the best condition by using EQ. 5.33.

5.3.5 Computational Steps

This section summaries the computation steps for the AUR adjustment process in order to define the Adjusted AUR(AAUR). The required steps to compute an AAUR are as follows:

- Step 1 Define input fuzzy set A*(measure degree of factor i)
- · Step 2 Find primary fuzzy set ,A, from a rule base
- Step 3 Find N value based on the hedge operators
- Step 4 Find B* by applying N to B using EQ.5.27
- Step 5 Compute fuzzy mean of B* using EQ.5.31.
- Step 6 Repeat step (1) to (5) until all factors are taken into account.
- Step 7 Find AAUR using EQ.5.33.

Fig. 5.9 shows this process.

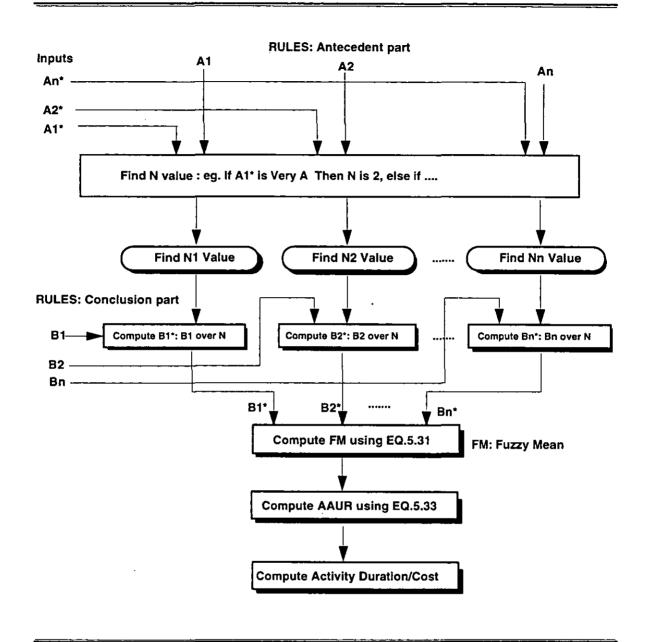


Fig. 5.9 Computational Steps

It is impractical to implement this process by hand calculations, since the calculation process to define AAUR involves heavy arithmetic operations. For this reason, a computer program has been written to implement FAURA proposed in this chapter. The program was written using the Turbo Prolog language to build a shell structure on an

IBM-PC as a research tool. The shell structure means a rule based system which has empty rule base. Thus, later, if a user fills the rules with a specified format according to the shell structure, then the system is ready for use. Appendix E shows the flowchart and the program list.

This completes the necessary tasks to design a fuzzy rule based system as shown in Fig 5.3 in section 5.3.

5.4 Summary

In this chapter, the methodology to deduce Adjusted AUR from the observed factors' influence on an activity is introduced. This was formulated by the fuzzy rule based system named FAURA. Based on this system, it is possible to determine the most likely AUR under a given set of factors' influence. However, testing and evaluation of the practicality of the proposed methodology requires more detailed analysis. This will be examined in chapter 6.

One of the most important achievement in this chapter is that the proposed method provides a formalised way of utilising subjective human expert knowledge for solving AUR adjustment problem that are inherent with uncertainty. This was achieved by FAURA which consists of the fuzzy production rules and the compatibility inference method.

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6.1 Introduction

The heuristic approach for the determination of activity time and cost was formulated by using the fuzzy rule based system(FAURA) in chapter 5. However, it is important to assess whether the system is an accurate representation of the real world being investigated. With this view, this chapter analyses the reliability of FAURA by examining the overall procedures used to generate adjusted AUR and activity duration/cost. The hypothetical bricklayer's activity with the five major qualitative factors are used to demonstrate the full potential of FAURA.

This chapter begins by examining the process required to build the rule base. The next section contains the verification analysis used to check the correctness of the reasoning process. In the third section, the sensitivity analysis is carried out to examine the behaviour of FAURA.

6.2 Building Rule Base

The purpose of this section is to examine the overall process of building a rule base for FAURA. In section 5.3.1 in chapter 5, the basic concept for building a rule base for FAURA was introduced. With this concept, this section demonstrates the steps(process) needed to build the rule base by using a bricklayer's activity. At same time, this process can provide an example of how users can build a rule base for their need. The analysis is carried out by using the rule base established in this section. This section is organised in the four subsections as follows:

- Rank Order of Factors
- Collection of rules
- Grade Scale of Linguistic Value
- Generating Fuzzy sets

6.2.1 Rank Order of Factors

The purpose of this task is to define the relative rank order among the factors as defined in Fig.3.3 in chapter 3. The relative rank order indicates a factor's degree of impact on activity j relative to others. For instance, even though all factors are measured as having the same degree, one factor might impact on the activity j more significantly than others. In this respect, a user can define the relative rank order after gathering information from several site manager. Horner's(1990) study can be used to determine the relative rank order. Table 6.1 shows productivity losses caused by the factors.

(source: Horner 1990)

Category(Factors) Productivity Loss(%)

Category (1 actors)	1 Toductivity 2033(70)
Management related(F3)	19%
Site related(F2)	22%
Design related(F1)	50%
Weather related(F4)	9%

Table 6.1 Relative Rank Order

Note that a crew related factor is added, since Horner study does not consider.

Based on this information, it is possible to define the relative rank order used in this study.

The relative rank order can be finalised as follows:

$$F1 > F2 > F3 > F4 > F5$$
(6-1)

where > means the greater influence,

F1 = Design Factor,

F2 = Site Factor.

F3 = Management Factor,

F4 = Weather Factor,

F5 = Crew Factor.

Suppose that a user defines the relative rank order as shown in EQ 6.1, this can then be used to assign ranges for the fuzzy sets used in the rules. This will be discussed in the next section. This rank order is only for the bricklayer's activity. However, the differing nature of activities such as concrete, steel frame, earth work etc. may have their own distinct rank orders since the nature of these jobs is completely different that of the bricklayer's job.

6.2.2 Generation of Rules

In order to build rule base, it requires collection of a large volume of information regarding the causal relationship from field experts. It is assumed that site managers(planners or estimators) who have more than 10 years of practical experience in masonry work are capable of providing the fuzzy information regarding the causal relationship as defined in the section 3.4 in chapter 3. Once the required information is

collected, then this can be used to build a rule base. Table 6.2 shows the example rules used in FAURA rule base.

Fi	IF(DF)	THEN(AUR)		
Fl:	If F1 is good	Then AURj is low 1		
Design	If F1 is medium	Then AURj is medium		
Factor	If F1 is bad	Then AURj is high 1		
F2:	If F2 is good	Then AURj is low 2		
Site	If F2 is medium	Then AURj is medium		
Factor	If F2 is bad	Then AURj is high 2		
F3:	If F3 is good	Then AURj is low 3		
Management	If F3 is medium	Then AURj is medium		
Factor	If F3 is bad	Then AURj is <i>high 3</i>		
F4:	If F4 is good	Then AURj is low 4		
Weather	If F4 is medium	Then AURj is <i>medium</i>		
Factor	If F4 is bad	Then AURj is high 4		
F5:	If F5 is good	Then AURj is low 5		
Crew Factor	If F5 is <i>medium</i>	Then AURj is <i>medium</i>		
	If F5 is <i>bad</i>	Then AURj is high 5		

Table 6.2 Example Rules

6.2.3 Ranges for Linguistic Terms

Once the linguistic terms are collected according to the rule format as shown in Table 6.2, the user should define the ranges for each of the linguistic terms used in the rules, to generate the fuzzy set(refer section 5.3.1.4 for the ranges in more detail). For demonstration purposes, the fuzzy system being developed in chapter 5 uses an activity called 'Ex.Wall - WS1 - Brick/Block'(refer Fig. 4.9 in chapter 4 more detail). For this activity, the Standard AUR(SAUR) is assumed to be 3.5 MH/M². This value is then used as a standard value for assigning the ranges for each linguistic terms as shown in Table 6.2.

Two considerations have to be addressed regarding when defining the ranges for the linguistic terms in general. First, it has to be based on the *ceteris paribus* assumption which means that when we are assigning a range for the particular factor, the remain other factors should be considered as normal(average) condition(Flanagan 1987). For example, when defining a range for the linguistic term, *high* AUR, under a bad design factor influence, the other factors such as site condition, weather condition, etc. are treated as normal(average) condition. Second, it is assumed that each factor is independent of all others(Carr 1991). In other words, there is no interaction among factors(refer assumptions in section 3.3.2 in chapter 3).

For the determination of the ranges for each fuzzy set, it requires some guide line so that the ranges can be assigned according to this. In this respect, Horner's study shown in table 6.1 can be used as the basis to assign the ranges for each fuzzy set. The design factor is the one which causes the greatest variability in AUR compared to other factors, hence the highest weight can be given to this factor. Similarly, the ranges for other factors can be

assigned according to EQ.6.1. The determination of ranges are usually based on the users subjective judgement with help form expert. For the purposes of this experiment, the following ranges are used in this study to represent the linguistic terms(*High1*, *High2*,..., *Medium*, *Low1*, *Low2*....) used in the rule base as shown in table 6.2. Fig.6.1 shows the ranges for the high linguistic term section.

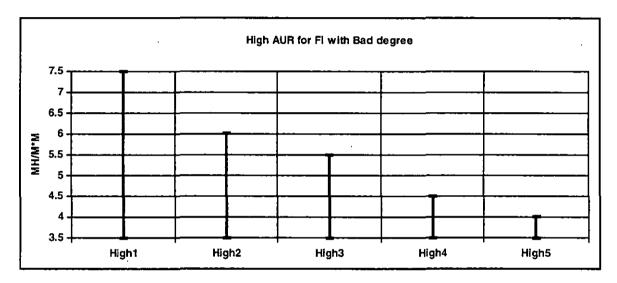


Fig. 6.1 Ranges for the High AUR

Fig. 6.1 shows the ranges for the high section AUR when all factors have a **bad** degree. For example, the category *High 1* represents the variability of AUR under bad design influence. In this case, the range from 3.5 to 7.5 MH/M² is used to represent the linguistic term, *High 1*.

Similarly, Fig. 6.2 shows the ranges for the low section AUR when all factors have a Good degree. For the low section, the range for the linguistic term, *Low 1*, is mapped out, with a decremental scale of 0.25 MH/M². Ranges for Low 2 - Low 5 are determined relative to this. In the case of all factors having average condition, the range from 3.0 to 4.0 MH/M² is used to represent the linguistic term, *Medium AUR*.

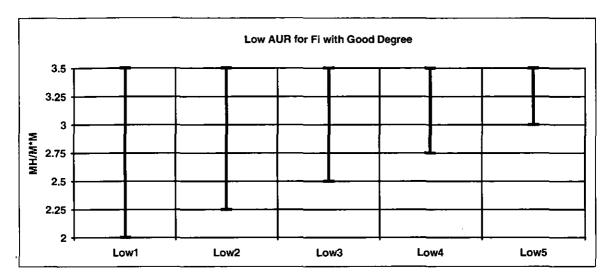


Fig.6.2 Ranges for the Low AUR

6.2.4 Fuzzy Set Generation

Once, the ranges for each linguistic term used in the rules are defined as shown in Fig. 6.1 and 6.2, then the lower limit(α), upper limit(γ) and centre(β) point from each range can be defined. After these parameters are defined, the fuzzy sets can be generated by using the Zadeh's standard membership functions as described in section 5.3.1.4 in chapter 5. The fuzzy sets are plotted in Fig.6.3. These are generated by the 'Curve. C' computer program written in this study(refer Appendix D) and the fuzzy sets data are stored under a specified sub directory for the reasoning purpose. Each line in Fig.6.3 indicates the fuzzy sets used in the rule base in table 6.2. The Y axis represents membership values and the X axis represents AUR.

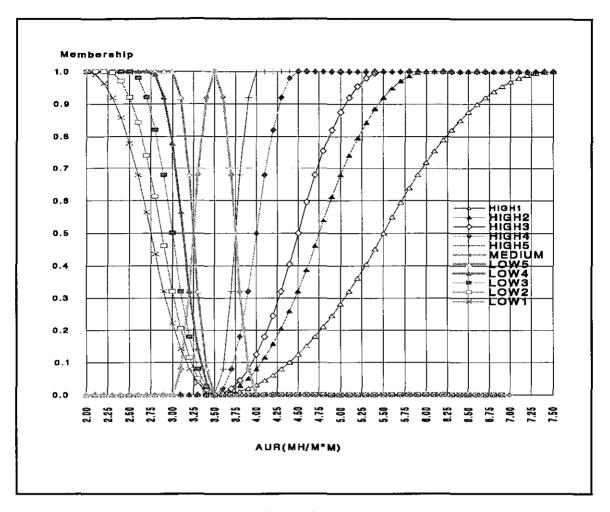


Fig. 6.3 Fuzzy Sets in Rule

6.2.5 Discussion

This section demonstrates the procedures in building a fuzzy rule base. It is obvious that the accuracy of fuzzy sets defined is directly related to the accuracy of the inference results. In attempting to build a prototype rule based system, the information used to build a rule base may be inappropriate, or a mis representation of a real life situation in some cases. However it is also important to note that this inaccuracy can be gradually reduced as more experience is gained.

6.3 Verification Analysis

This section describes the computational process used to generate an adjusted AUR. The purpose of this section is to verify the accuracy of the inference process for the fuzzy system proposed in chapter 5.

6.3.1 Example

では、これには、100mmのでは、1

For the verification purpose, the following example is designed to demonstrate the inference process. Fig. 6.4 shows the example input and output.

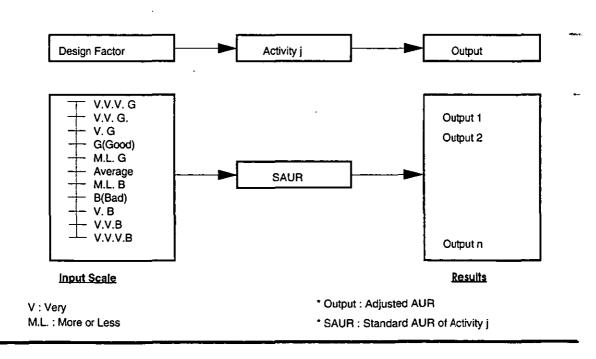


Fig. 6.4 Example Input and Output

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A. Input Factor

For demonstration purposes, only a design factor is used and the degree of this factor is

varied to generate the output which is the adjusted AUR. The method of designing the

linguistic input value was discussed in Section 5.3.2 in chapter 5. Based on this, the 11

linguistic scale is designed to measure the degree of design factor and used as input values.

B. Activity

The standard external brick/block wall activity is used(refer Fig. 4.9 in chapter 4).

Activity Name: External Wall-Brick/Block

Activity Quantity: 1000 M²

Wages: 7.06 per Man Hour(MH)

The Standard AUR(SAUR) for this activity was estimated as 3.5 MH/M² from the

existing estimating sources(Wessex data base). The SAUR means the average AUR based

on the assumption that the activity will be carried out within an average project

environment.

C. Rule

The example rules used to generate the outputs are:

Rule 1:

If Design Factor is **Bad** Then AUR is **High1**

Rule 2:

If Design Factor is **Good** Then AUR is **Low1**

The fuzzy sets in the consequent part of rule, *High 1* and *Low1*, are defined in Fig. 6.3.

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6.3.2 The Results

With these rules and the input values as shown in Fig.6.4 for the design factor, the inference results are shown in table 6.3. This is based on the hedge operators as mentioned in section 5.3.3.4 in chapter 5.

Input : Ai* = Bad(or Good)	Output : Bi* = High i(or Low i)
Input 1 : A1* = Bad(Good)	B1* = High i, (Low i)
Input 2 : A2* = Very Bad(Good)	$B2* = (High i)^2, (Low i)^2$
Input 3: A3* = Very Very Bad(Good)	$B3* = (High i)^4, (Low i)^4$
Input 4: A4* = Very Very Very Bad(Good)	$B4* = (High \ i)^8, (Low \ i)^8$
Input 5 : A5* = More or Less Bad(Good)	$B5* = (High i)^{0.5}, (Low i)^{0.5}$

Table 6.3 Output Fuzzy Sets

Fig. 6.5 shows the output fuzzy sets from the inference results under the 5 adverse input values for the design factor. This was generated using EQ.5.27 and 5.28 in section 5.3.3.4 in chapter 5. Each curve in Fig. 6.5 represents the output fuzzy sets (B1*,B2*,..,B5*) which interpret the linguistic terms such as Very High,...,More or Less High under the five adverse input values. The Y axis represents the membership value. The X axis represents the member of fuzzy set, Bi*, which is the AUR.

Likewise, Fig.6.6 shows the output fuzzy sets under the favourable design factors inputs. The fuzzy set, B1*(Low), represents the linguistic term Low. Fig.6.5 and Fig.6.6 are only two sets of fuzzy outputs from the inference results under adverse and favourable design factor inputs.

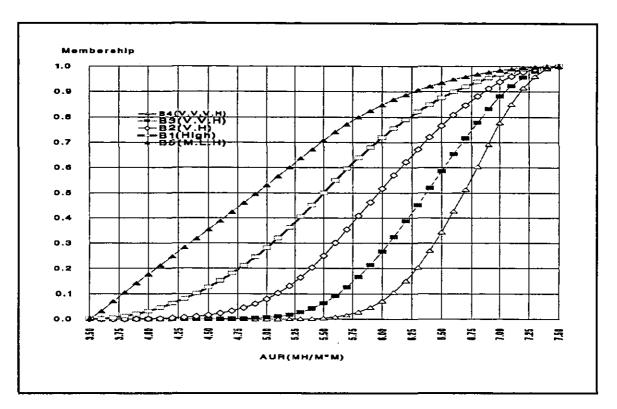


Fig.6.5 Output Fuzzy Sets under Adverse Design Conditions

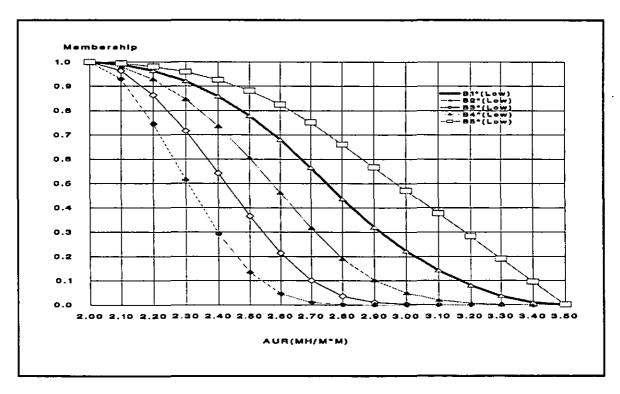


Fig.6.6 Output Fuzzy Sets for Favourable Design Condition

CHAPTER 6

6.3.3 Interpretation of Output

Table 6.4 shows the process used to calculate the adjusted activity time and cost under various degree of design factor in the high section. Column 2 in table 6.4 shows the interpretation of each output fuzzy set as shown in Fig. 6.5 and 6.6. Once output fuzzy set is defined, then one single numerical value which can portray the each output fuzzy set is required. This can be calculated by using the fuzzy mean(FM) operation(refer EQ.5.31 in chapter 5). This value is used to represent the adjusted AUR(AAUR) and is shown in the column 3. The AAUR value is then used to calculate adjusted activity duration/cost. Column 4 and 5 show the activity duration and cost respectively. The activity cost represent labour cost only.

Quantity(M*M) : 1000

Wages

: 7.06

SAUR(MH/M*M): 3.5

Output Fuzzy Sets	Membership Function(ய/u) ¹	AAUR ²	AD(MH) ³	AC ⁴
. (1)	(2)	(3)	(4)	(5)
B1*(High)	0/3.5, 0.031/4, 0.125/4.5,	6.362	6362.00	£44,915.72
	0.281/5, 0.5/5.5, 0.719/6,			
	0.875/6.5, 0.969/7, 1/7.5		·	
B2*(Very High)	0/3.5, 0.001/4, 0.016/4.5,	6.616	6616	£46,708.96
	0.079/5, 0.25/5.5, 0.517/6,			
	0.766/6.5, 0.939/7, 1/7.5			

	<u> </u>		· · · · · · · · · · · · · · · · · · ·	
B3*(Very Very High)	0/3.5, 0/4, 0/4.5, 0.006/5,	6.830	6830.00	£48,219.8
	0.063/5.5, 0.267/6, 0.586/6.5,	i		
	0.882/7, 1/7.5	-		
B4*(V.V.V High)	0/3.5, 0/4, 0/4.5, 0/5, 0.004/5.5,	7.005	7005.00	£49,455.3
	0.071/6, 0.344/6.5, 0.777/7,		:	
	1/7.5			
B5*(More or Less High)	0/3.5, 0.141/4, 0.354/4.5,	6.1	6100.00	£43,066
	0.530/5, 0.707/5.5, 0.848/6,		i	
	0.935/6.5, 0.984/7, 1/7.5			

1:μ: Membership Value of u

u: Member of a fuzzy set

2. AAUR: Adjusted AUR Using the Fuzzy Mean Operation(refer EQ.5.31)

3. AD: Adjusted Duration = AAUR × Quantity

4. AC: Adjusted Cost = AD × Wages

Table 6.4 Outputs For High Section

Likewise, table 6.5 shows the process for the low section output interpretation process.

Quantity(M*M) : 1000

Wages : 7.06

SAUR(MH/M*M) : 3.5

Output Fuzzy Sets	Membership Function(μ/u) ¹	AAUR ²	AD(MH) ³	AC ⁴
B1*(Low)	1/2, 0.92/2.3, 0.778/2.5, 0.436/2.8,	2.409	2409	£17,007.54
	0.222/3, 0.036/3.3, 0/3.5			

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	r			
B2*(Very Low)	1/2, 0.846/2.3, 0.605/2.5, 0.19/2.8,	2.315	2315	£16,343.9
	0.049/3, 0.001/3.3, 0/3.5			
B3*(Very Very Low)	1/2, 0.716/2.3, 0.366/2.5,	2.233	2233	£15,764.98
	0.036/2.8, 0.002/3, 0/3.3, 0/3.5			
B4*(V.V.V Low)	1/2, 0.513/2.3, 0.134/2.5,	2.168	2168	£15,306.08
	0.001/2.8, 0/3, 0/3.3, 0/3.5			
B5*(More or Less Low)	1/2, 0.959/2.3, 0.825/2.5, 0.66/2.8,	2.508	2508	£17,706.48
	0.471/3, 0.19/3.3, 0/3.5			

μ: Membership Value of u

u: Member of a fuzzy set

2. AAUR: Adjusted AUR using the Fuzzy Mean Operation(Refer EQ.5.31)

3. AD: Adjusted Duration = AAUR × Quantity

4. AC: Adjusted Cost = $AD \times Wages$

Table 6.5 Outputs For Low Section

From table 6.4 and 6.5, the AAUR values are plotted in Fig. 6.7 to show the sensitivity of the AAUR under the various degrees of the design factor. The Y axis indicates the AAUR as output values from the inference results and the X axis indicates the degree of design factor as input values. Fig.6.7 shows the variability among the AAUR values. The AUR ranges from 7.005 MH/M² for having extremely bad design to 2.168 MH/M² for having extremely good design. Whereas if a design is normal, then AUR is 3.5 MH/M².

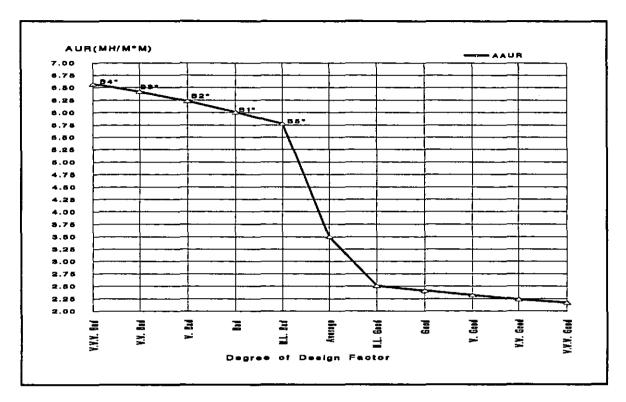


Fig. 6.7 Sensitivity of AAUR Values

6.3.4 Discussion

Form Fig.6.7, three discussion points can be made. There are:

- A) AUR variability under adverse design factor influence
- B) AUR variability under favourable design factor influence
- C) The gap between SAUR and B5*(More or Less High)

Firstly, the inference results(B1*,B2*,..B5*) under adverse design factor input values shows an incremental rise about 0.3 MH/M² from B5*(More or Less high). These values are calculated by using the fuzzy mean(EQ.5.31) operation. Each point in Fig. 6.7

indicates the impact, on AUR, of a defined proportionate variation in design factor. For example, it can be seen from Fig. 6.7 that if the design of an activity j is extremely bad(V.V.V.Bad), then the resulting AUR(B4*) will be about 2 times higher than the Standard AUR.

Secondly, the inference results(B1*,B2*,..,B5*) under favourable design factor input values shows an incremental rise about 0.1 MH/M² from B4*(V.V.V Low). This implies that favourable design factor input values result in smaller changes on outcomes. This is due to the fact that no matter how good a design, there will still be a minimum required time to do the job. Therefore, the favourable design condition can be represented by the single input value, *Good*, since there is very little difference in outcomes from various input values such as very very good design, more or less good design, etc.

Thirdly, there is a big gap between SAUR(3.5MH/M²) and B5*(more or less high)(6.1MH/M²). This is due to the fact that the value of B5* is deduced from the range used in the B1*(3.5-7.5). This means that if we use smaller ranges, for example a new range, 3.5-4.5, then obviously this gap will be narrower. However, since the design factor is the most influential factor, consequently the variability of AUR will be greater. This aspect are reflected in the rage as shown in Fig. 6.1. For this reason, the range for the High 1 under bad design influence is the widest than the others(refer Fig.6.1), The results in Fig. 6.7 reflects that the design factor is most influential factor on the AUR as shown in table 6.1.

However, when we are including the remaining factors such as management, weather, site, crew factor at same time, the variability of AUR will be further compounded by mutifactor interaction. Further discussion regarding this aspect is provided in the next section.

6.4 Sensitivity Analysis

This section examines the validity of FAURA. The validity means whether the inference results yield an appropriate solution or not. The fuzzy reasoning approach, this was solved by using hedge operators such as dilation and concentration(refer section 5.3.3.4). However, whether using the hedge operators yields appropriate result can be examined by the use of sensitivity analysis. The purpose of sensitivity analysis here is to examine the output values when the values of Fi (degree of factor) are increased or decreased according to the pre-defined linguistic scales. Through this analysis, it is possible to examine the potential application of the hedge operators as a solution to define the Adjusted AUR(AAUR) under a given set of factors influence. The following sections examine this aspect.

6.4.1 Example

For the sensitivity analysis, the following example is used as shown in Fig.6.8.

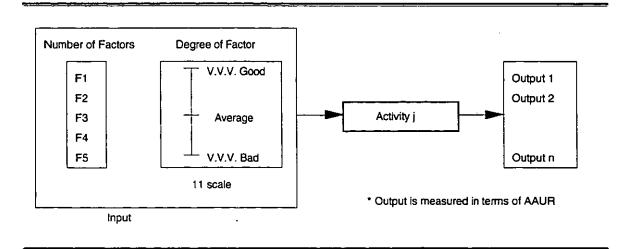


Fig. 6.8 Input and Output

The five factors are used as input variables as defined in chapter 3 to represent a unique project environment. This is shown in Fig.6.9.

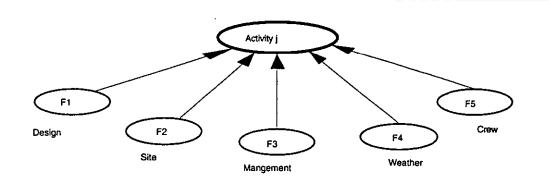


Fig. 6.9 Factors Influencing on Activity j

The degree of each factor is assumed to be as shown in Fig. 6.10. The linguistic scale shown in Fig. 6.10 will be used as the input values to FAURA to generate Adjusted AUR. Thus the user can measure a factor under consideration according to this format.

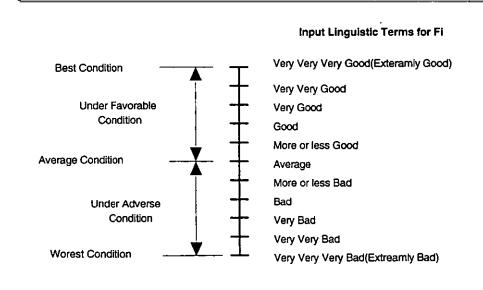


Fig. 6.10 Scale of Input Linguistic Terms

The same activity as defined in the section 6.3.1 is used in this analysis. The medium size of activity is used. The rule base for this analysis is as shown in table 6.2.

6.4.2 Results

This section describes the resulting data generated from FAURA using the example as defined in the Fig. 6.9.

A. The Output Values

Table 6.6. shows the calculated Adjusted AUR(AAUR) values for the individual factors having a certain degree as input values. Column 1 shows the input value which is the measure of factor i(i=1,2,..,5). Column 2 through 6 shows the AAUR values to the corresponding input value in column 1. Column 7, the total impact, is the measure of cumulative factors' impact on activity j by using EQ. 5.33.

Input Value	Design	Site	Management	Weather	Crew	Total
DF	Factor(F1)	Factor(F2)	Factor(F3)	Factor(F4)	Factor(F5)	Impact
(1)	(2)	(3)	(4)	(5)	(6)	(7)
V.V.V. Good	2.168	2.356	2.603	2.834	3.051	2.602
V.V. Good	2.233	2.411	2.646	2.867	3.073	2.646
V. Good	2.313	2.478	2.7	2.907	3.1	2.6996
Good	2.409	2.558	2.764	2.955	3.132	2.7636
M.L. Good	2.508	2.641	2.829	3.004	3.164	2.8292
· V.V.V. Bad	7.005	5.702	5.267	4.397	3.961	8.389

					· · · · · · · · · · · · · · · · · · ·	
V.V. Bad	6.83	5.592	5.18	4.354	3.939	8.104
V. Bad	6.616	5.458	5.072	4.3	3.913	7.760
Bad	6.362	5.3	4.945	4.236	3.881	7.362
M.L. Bad	6.1	5.135	4.814	4.171	3.85	6.962

3.5

3.5

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3.5

Table 6.6 The Sensitivity Table

3.5

These results were generated by FAURA without any other calibration of the rule base as shown in table 6.2.

B. The Sensitivity of Output

3.5

CHAPTER 6

Average

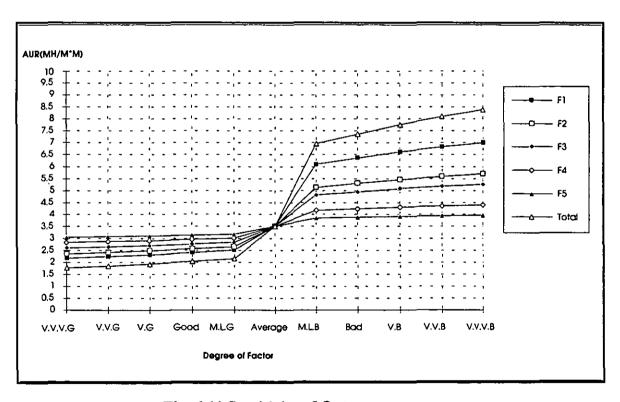


Fig. 6.11 Sensitivity of Output

Fig. 6.11 displays the sensitivity of output which is the relationship between Adjusted AUR(as output) and the five factors(as input). This shows the changes of AUR as a function of Degree of Factor(DF). It also shows that the favourable DF causes the lower AUR value, whereas, the adverse DF causes the higher AUR. The medium value of AUR, however, remains as constant value, 3.5 MH/M². This implies SAUR represents the AUR value under all factors with average conditions. Each factor has its own output curve. This indicates the impact on AUR according to the relative ranking order among factors as defined EQ.6.1 in section 6.1.1. For example, the sensitivity of AUR under the design factor's influence is the highest.

C. The Total Output Analysis

Fig. 6.12 displays the AAUR which is the synthesis of the five factors(such as design, management,...,etc.) impact on activity j simultaneously. Each point in Fig. 6.12 represents the sum of the output points in Fig. 6.11. Each point is calculated by using EQ.5.33 in section 5.3.4.2. The X axis represents the overall measure of five factor and the Y axis represents the AAUR under the five factors impact. This provides information on the magnitude of variation in AUR which can be expected by the given input values. The AAUR ranges from 8.389 MH/M² for the worst degree of each factor's combination, i.e. all factors being V.V.V.Bad to 2.6024 MH/M² for the best degree of each factor's combination, i.e. all factors being V.V.V.Good. Whereas, the Standard AUR is 3.5 MH/M² which means all factors having the average degree. The lowest AUR assumes that the most favourable scenario for each factor, whilst the highest AUR assumes that the worst scenario for each factor.

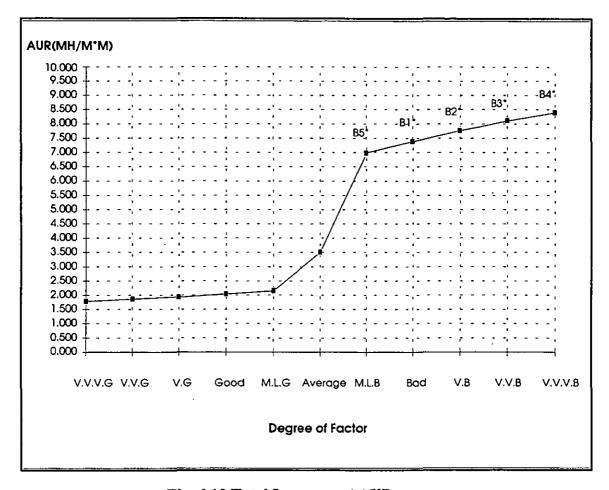


Fig. 6.12 Total Impact on AAUR

6.4.3 Discussion

From Fig.6.12, Two discussion points can be made. These are:

- A) Output analysis,
- B) Validity of results.

A. Output Analysis

Similar observations in relation to the output analysis can be made as discussed in section 6.3.4.

Firstly, the inference results under adverse combination of factors' influence shows an incremental scale rise of about 0.4 MH/M² from B5*(more or less high). These values are calculated by using the EQ.5.33 in section 5.3.4.2 in order to take into account cumulative effect. Each point in Fig. 6.12 indicates the total impact on AUR under 5 factors influence based on the predefined input scale as shown in Fig.6.10. For example, it can be seen from Fig. 6.12 that if all factors are measured as extremely bad(V.V.V.Bad), then the resulting AUR(B4*) will be about 2.4 times higher than the Standard AUR(SAUR). Similarly, B3* to B1* are 2.3 to 2.1 times higher than SAUR. This means that the hedge operators used in the inference process are acting properly in the sense that 'the more X is A, then the more Y is B' as mentioned in section 5.2.1.

For the favourable input factor values such as V.V.V. Good, V.V. Good, V.Good, More or Less Good and Good, there is little variation among the resulting outputs as shown in table 6.6. This reveals that the input linguistic scale for the favourable factors condition as shown in Fig. 6.10 is not sensitive. The reasons for this was mentioned in section 6.3.4. Consequently, it is not desirable to use the linguistic hedges for the favourable factor condition.

Thirdly, there is a big gap between SAUR(3.5 MH/M²) and B5*(6.96MH/M²). This indicates that the difference between these two points is almost two times higher than the value of SAUR. This is rather unsatisfactory outcome. The reasons for this wide gap is contributed to the ranges used for the high section, for example high 1, high 2,..., high 5, as

shown in Fig.6.1. Thus if a user want to reduce this gap in a smaller scale, then all the ranges used in Fig. 6.1 have to be reduced until the satisfactory outcome is found.

B. Validity

However, the question of model validation remains, i.e., does FAURA produces valid results? The outcome of FAURA is only as good as the rule base used upon which these inference results are based. Thus, as long as the rule base is accurate, consequently the results will also be accurate. However, the accuracy of rules employed in the rule based is of minor important, since the rules can be modified and updated at any time whenever new facts or more precise knowledge are gathered. What is more important is to design a formalised system that addresses uncertainty explicitly, and gives the decision maker factual information on which to base his decisions. This is achieved by FAURA.

To prove the accuracy(acceptability) of the model, it relies on a comparison between actual outcomes and model outcomes. This process requires the collection of large volumes of actual data from construction sites. However, at this stage, it not possible to examine the validation of the system, since the collection of sufficient data from the field would involve an extensive study in its own right. Therefore, the validation of system has been left to further studies. For this reason, FAURA is not presented as a final operational model, rather as a proto-type system. As experience and evidence is accumulated, the system will become more reliable and mature.

Nevertheless, these results show a more realistic approach than a single point estimate in dealing with the prediction of the most likely value of AAUR with a range between the lowest AUR and highest AUR, given that a certain degree of factors exist.

6.5 Adjustment of Output

As mentioned in the previous section, it is not possible to prove the accuracy of the system output, since this study is based on the theoretical situation. It is, therefore, worthwhile to discuss the method of adjustment for the outcome of the system for a situation where the inference results may not be satisfactory.

6.5.1 The Method of Adjustment

There are three possible methods of modification:

- Modification of the rules
- Modification of the hedge operators
- Introduction of coefficient values

A. Modification of Rule

The first cases is to redefine the fuzzy sets used in the rules. There are two possible ways to the redefine fuzzy sets. The first is to adjust the membership values of the fuzzy sets. This can be done by using different standard membership functions such as triangular or trapezoidal membership functions or using subjectively assigned membership values. However, previous fuzzy set application studies(Ayyub and Haldar,1984, Kangary,1987) show that the membership values have little effect on the final result. More specifically, the outcome is not sensitive to changing the membership values by using the triangular membership function, Zadeh's standard membership function or subjectively assigned membership value. This aspect has advantages in using the standard membership functions

such as triangular or Zadeh's standard membership functions to generate the fuzzy set used in the rule base.

However, the scale used in a range directly impacts on the inference result. For example, for a fuzzy set, *High*, it is possible to increase or decrease the range of this fuzzy set. However, there are no standard, or models to define low limit, upper limit and centre point required to generate the fuzzy set. Therefore the process relies on expert's subjective opinion. This is an inherent weakness in using fuzzy set theory.

B. Modification of Hedge Operators

The second possibility is to modify the values of hedge operators. For example, if the results generated by the hedge operator such as *More or Less* is not produce expected output, then this can be modified by increasing or decreasing the exponential value of *More or Less*, 0.5. Likewise, the *very* hedge operators can be modified. For example, it can be increased by modifying the exponential power by 4 instead of 2. However, when the value of the exponential power is becomes greater, the results from the FM operation(refer EQ.5.31) approach the upper limit value of the range which is not yield a satisfactory outcome. This approach does not provide a sensible solution.

C. Using coefficient

The adjustment can be done by introducing adjustment coefficient values, ωi . This allows users to modify the inference result by using the coefficient value, ω , by increasing or decreasing the value until a suitable solution is found. For example, if the results in Fig. 6.12 are too low(or high) than might be expected, then the value of ω can be increased(or decreased) until an approximate solution is found. This is a simplistic way to modify the system output. Thus, this approach has been adopted to modify the results.

6.5.2 Adjustment Process

The method using the coefficient value is chosen for the adjustment of the outputs in Fig.6.11. This is based on the assumption that the ranges used in the fuzzy sets are accurate. Further, the output under the worst combination of factor's influence is assumed to be reasonable. Thus, the adjustment can only be made for other outputs under adverse conditions, because the output values under favourable combinations of factor' influence are not significant. The overall impact curve, denoted A0, as shown in Fig.6.11 is used as a basis for the adjustment. As shown in Fig. 6.11, a user may want to increase the original increment scale, i.e. 0.4 MH/M². Further, a user wants to reduce the gap between SAUR and B5*(more or Less High). This can be done by applying the adjustment coefficient value, ω, as the exponential power to the value of each point(output) in A0. Let each point in A0 denotes FMi.

	A0	Al	A2	A3
Average	FM1	(FM1) ^{ω11}	(FM1) ^{ω12}	(FM1) ^{ω13}
M.L.B	FM2	(FM2) ^{ω21}	(FM2) ^{ω22}	(FM2) ^{ω23}
Bad	FM3	(FM3) ^{ω31}	(FM3) ^{ω32}	(FM3) ^{ω33}
V.B	FM4	(FM4) ^{ω41}	(FM4) ^{ω42}	(FM4) ^{ω43}
V.V.B	FM5	(FM5) ^{ω51}	(FM5) ^{ω52}	(FM5) ^{ω53}
V.V.V.B	F <u>M6</u>	(FM6) ^{ω61}	(FM6) ^{ω62}	(FM6) ^{ω63}

Table 6.7 Adjustment Table

The three adjustment options, A1, A2 and A3 are used. A1 uses 0.5 decremental scale starting form the coefficient value of 0.9 based on the FM5. Similarly, A2 uses 0.5

decremental scale starting from the coefficient value of 0.95 based on the FM5. Finally, A3 uses 0.4 decremental scale starting form the coefficient value of 0.98 based on the FM5. These options are selected by try-error approach without a formalised method. These are summarised in table 6.8.

	A0	A1	A2	A3
Average	1	1	1	1
M.L.B	1	0.75	0.8	0.86
Bad	1	0.8	0.85	0.9
V.B	1	0.85	0.9	0.94
V.V.B	1	0.9	0.95	0.98
V.V.V.B	1	11	1	1

Table 6.8 Adjustment Coefficient Values

Using these coefficient values, the adjusted AAUR is summarised in table. 6.9.

	A0	Al	A2	A3
Average	3.500	3.500	3.500	3.500
M.L.B	6.962	4.286	4.723	5.306
Bad	7.362	4.938	5.457	6.030
V.B	7.760	5.707	6.322	6.862
V.V.B	8.104	6.574	7.299	7.772
V.V.V.B	8.389	8.389	8.389	8.389

Table 6.9 Adjusted Values

These results are depicted in Fig.6.13.

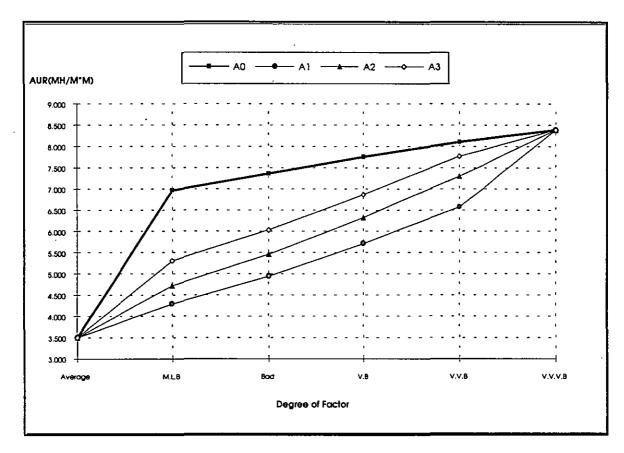


Fig 6.13 Adjustment Results

The selection of an appropriate adjustment option is dependent on actual data gather from many site under different conditions. However, it is not possible to define which option provides the best representation, since this study is limited to the theoretical situation only.

6.5.3. Adjusted activity duration/Cost

The results of the adjusted activity duration/cost under the combination of the five factors impact on activity j are summarised in table 6.9. Note that the activity costs are labour only costs. The comparison can be made based on A0 with three other adjustment options.

Activity Quantity: 1000 M²

Wages: 7.06

		AAUR			Activity Duration(MH) ¹			Adjusted Activity Cost ²				
DF	A0	A1	A2_	A3	AD0	AD1	AD2	AD3	AC0_	AC1	AC2	AC3
Good	2.764	2.764	2.764	2.764	2764	2764	2764	2764	£19,514	£19,514	£19,514	£19,514
Average	3.500	3.500	3.500	3.500	3500	3500	3500	3500	£24,710	£24,710	£24,710	£24,710
M.L.B	6.962	4.286	4.723	5.306	6962	4286_	4723	5306	£49,153	£30,260	£33,343	£37,460
Bad	7.362	4.938	5.457	6.030	7362	4938	5457	6030	£51,97 <u>5</u>	£34,865	£38,525	£42,569
<u> </u>	7.760	5.707	6.322	6.862	7760	5707	6322	6862	£54,787	£40,290	£44,636	£48,449
V.V.B	8.104	6.574	7.299	7.772	8104	6574	7299	7772	£57,212	£46,411	£51,529	£54,867
V.V.V.B	8.389	8.389	8.389	8.389	8389	8389	8389	8389	£59,225	£59,225	£59,225	£59,225

^{1,} AD : AAUR * Quantity 2: AC: AD * Wages

Table 6.10 Adjusted Activity Duration/Cost

Fig. 6.14 displays the adjusted activity cost using the three adjustment options. The costs range form £59,225 for the worst factors impact to £19,514 for the best factors impact on the activity j. Whilst the standard activity cost is estimated as £24,710.

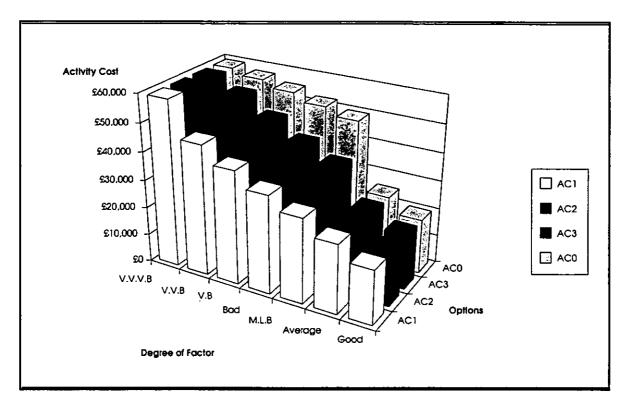


Fig.6.14. Adjusted Activity Cost

6.6 Summary

This chapter demonstrates and analyses a fuzzy rule based system approach to estimate activity duration/cost under the influence of various factors. The proto-type system, FAURA, was developed primary to examine two aspects which are:

 to examine the possibility using fuzzy set theory and fuzzy logic as a better solution for the qualitative nature of factors quantification problems in determining activity duration/cost; CHAPTER 6 ANALYSIS

 to formulate a systematic framework for utilising heuristic knowledge into a prototype system.

The analysis shows that a fuzzy rule based system approach provides a promising methodology to deal with vague(or uncertainty) contained in the causal relationship.

FAURA quantifies the impact of the qualitative factors and simplifies the adjustment process, since the user does not need to understand the underlying fuzzy set theory. A user needs only to input an assessment of factors according to the pre-defined input terms scale. The sensitivity analysis highlights that FAURA has the ability to model the complex relationship between factors and AUR and provides a rational framework for handling such tasks. It is also adaptable to the other types of estimation tasks subject to uncertainty as long as the rules are collected. This is a significant property of FAURA. However to make the system generic and applicable to other types of activities, further validation using actual data is needed.

Chapter 7: Conclusions and Recommendations

7.1 Conclusions	
7.2 Recommendations for Future	Work

7.1 Conclusions

7.1.1 Introduction

The objectives of this research as stated in section 1.4 were to:

- To investigate and propose a formalised method of utilising heuristic knowledge for the determination of activity duration/cost allowing for uncertainty for project planning and control purposes; and
- To examine the application of fuzzy set theory and fuzzy logic to implement the formalised method.

The primary objective of this research was to develop a systematic framework to quantify the impact of qualitative factors that are inherent with uncertainty in the activity duration/cost estimation process. This research clearly demonstrates the potential for applying fuzzy set theory to develop a formalised method of utilising heuristic knowledge in conjunction with a fuzzy rule based system. The findings and conclusions in respect of these objectives are described below.

7.1.2 Formalised Method of Utilising Heuristic Knowledge

A. Method of Generating Standard AUR(SAUR)

A method of generating SAUR has been proposed in chapter 4. The purpose of designing this system was to generate the SAUR so that an adjustment process can be initiated by using the SAUR. This provides a clear method to resolve the ambiguity in determining the SAUR for a specified activity. This process is based on the clear definition of activity and thereby identifying operations associated with an activity. In this way, the SAUR for the specified activity can be defined from an existing data base.

B. FAURA

The estimation of activity duration/cost involves the assessment of the impact of qualitative factors(QF) such as design, management, site, and numerous other factors. The QF are not directly measurable and have some degree of uncertainty in their impact on the activity. The quantification of the causal relationship in estimating project costs and durations has been left to the expert's subjective judgement without a formalised process in the past. FAURA provides the estimators(or planners) with a method to enhance this process.

The analysis in chapter 6 shows that FAURA is able to model and describe the vague causal relationships between the various qualitative factors and Activity Unit Rate(AUR) and can produce magnitude of variation in AUR from the worst scenario to best scenario for each factor. FAURA provides the decision-maker with valuable information on which to base his decision.

The strength of FAURA are as follows.

• It enables user to assess the impact of uncertainty factors on activity duration/cost.

- It provides a rapid and efficient means of calculating activity duration/cost.
- It provides a formalised way of utilising heuristic knowledge.

FAURA accomplishes these tasks by capturing expert knowledge regarding the causal relationship in the form of fuzzy production rules. Some of the unknown causal relationships can be deduced by using the fuzzy inference method.

7.1.3 Application of Fuzzy Set Theory

A. Standard Membership Function

Generating a fuzzy set, using subjectively assigned membership values as used in the previous studies, increases bias in the assigned membership values. Thus, it is more practical to use standard membership functions to define the fuzzy sets. In this way, the bias in assigning membership values can be reduced. However, the standard membership functions selected should clearly represent the meaning of the linguistic terms used in the system. In this study Zadeh's standard membership functions were used to interpret linguistic terms into fuzzy sets. The advantage of using these membership functions is that they convey a more appropriate interpretation of linguistic terms into fuzzy sets than the simplified linear membership functions such as triangular or trapezoidal membership functions. This is due to the fact that the membership functions of activity unit rate is more likely to be represented by non-linear membership functions such as Zadeh's membership functions.

B. Fuzzy Rules

Conventional rules(non-fuzzy rule) require a precise numerical value in a causal relationship. This approach has difficulties in justifying the accuracy of numerical values given by experts, particularly, when dealing with vague situations. Fuzzy rules can overcome these shortcomings by allowing for the use of linguistic terms to represent the fuzziness contained in causal relationships between qualitative factors and activity unit rate. A fuzzy production rule allows the inclusion of vagueness in a causal relationship, since it uses a linguistic term as a range rather than a single number. It provides a superior mechanism to capture uncertainties contained in a causal relationship. This approach provides a more practical solution for capturing uncertainties contained in the causal relationship. Moreover, it provides a much easier method for collecting knowledge and experience from an expert.

C. Fuzzy Inference

In the classical modus ponens inference, the input value must match the premise of the rule, otherwise this mechanism can not work. This requires the collection of a large number of rules in the rule base. However, the fuzzy modus ponens(or fuzzy inference), which is a generalisation of modus ponens allows the deduction of a new conclusion from a production rule and given input which are not necessarily the same as the premise of rule. In other words, it provides the ability to deduce unknown conclusions from some of the basic rules and a given input. This is a very desirable property of the fuzzy inference mechanism. This aspect of fuzzy inference makes it a more flexible and economical inference mechanism than the classical modus ponens.

In this study, the concept of compatibility measurement method proposed by Nafarieh and Keller was adopted as inference strategy for FAURA. This method is further simplified by

using Zadeh's hedge operators such as concentration and dilation operators to measure the compatibility between input value and the premise of the rule. In this way, the computational process to deduce the conclusion only requires a relatively simple formula, although the background theory is quite complex. This simplicity provides an efficient mechanism to design a fuzzy rule based system. This approach, by using Zadeh's hedge operators, provides a simple, practical technique which is able to deduce unknown conclusions from some of the basic rules and given inputs.

D. Difficulties in the Fuzzy Approach

Two difficulties are found when applying fuzzy set theory to developing a fuzzy rule based system. These are:

- Interpretation of the fuzzy sets,
- Determination of the ranges.

The first problem is the interpretation of linguistic terms in objective way. A linguistic term can be modelled by the fuzzy set. Once a fuzzy set is defined, then it requires the interpretation of fuzzy set into a single numerical value. Usually, the fuzzy sets are interpreted by the Fuzzy Mean equation. However, there is no guarantee that the Fuzzy Mean equation produces 100 % accurate interpretation of the fuzzy set into a single number, rather this is an approximate interpretation of a fuzzy set. This may creates some problems in validating the results. In such cases, the FM value can be used as the basis to adjust the results.

The second problem is the determination of accurate ranges for a fuzzy set. The determination of range for a fuzzy set is not a precise scientific exercise, since there is no a model or formula to define the range for a linguistic term. Hence the determination of a range has to be defined by the user's or expert's subjective opinion. Thus the accuracy of the range is obviously dependent on the level of knowledge of the user. This is undesirable property of fuzzy set theory. However, the problems caused by the inaccurate range can be gradually reduced as more experience is gained and through the learning process.

7.1.4 Limitations of Study

A. Validation of System

This study is based on a theoretical investigation into the causal relationships between qualitative factors and Activity Unit Rates. As such it has sought to establish fundamental methodologies which can be applied to formalise subjective procedures. It was recognised from the outset that the data required to validate such a system would require a data collection exercise in conjunction with work study techniques of a scale which was impossible to achieve within the time frame of this study. The collection of appropriate data was not attempted during the course of the research.

B. Overall Impact Measurement

As discussed in section 5.3.4.2, there is a need to have a method to sum the individual outputs in order to take into account their cumulative effect. For this reason, the following equation was introduced in section 5.3.4.2(considering 5 factors only).

$$AAUR = f(F_1, F_2,, F_5)$$

$$= (\theta_1 \times \theta_2 \times \theta_3 \times \theta_4 \times \theta_5)^{\lambda} \times S \qquad(7.1)$$

$$= (\frac{O_1}{S} \times \frac{O_2}{S} \times \frac{O_3}{S} \times \frac{O_4}{S} \times \frac{O_5}{S})^{\lambda} \times S$$

The purpose of EQ.7.1 is to take account of the multi-factor interaction on the activity j. The function of λ is to adjust the product of coefficient output values, θ , in EQ.7.1. This only represents a temporary solution until sufficient data can be collected to evaluate λ and as such requires further study.

7.2 Recommendations for Future Work

Although this research develops a systematic framework to quantify the impact of the qualitative factors in determining activity duration/cost, further investigation could enhance the current version of FAURA and provide a working system which can be used by practitioners.

1. Testing the FAURA on Live Project

Although, FAURA has been tested and analysed on a hypothetical bricklayer's activity, further validation using on live projects is required to make this system generic and applicable to other types of activities. FAURA should be used by planners or estimators before commencing a project, in parallel with conventional techniques such as PERT, Simulation models or others types of model for the purpose of measuring the accuracy of the FAURA.

2. Factor Measurement

For qualitative factor measurement in a more objective and systematic way, the Fuzzy Weighted Average(FWA) method can be incorporated into FAURA. This means FWA can be used as an input factor measurement mechanism. Therefore, the output from the FWA can be used as input for FAURA. A further study is required to design an interface facility to link FWA and FAURA.

3. Integrated System

FAURA should form part of a larger integrated system. The concept of an integrated system would consist of the three subsystems which are:

- Data base system
- Adjustment system
- Scheduling tools:

In this study, two separate systems are presented. Firstly, the method of generating SAUR is presented. This can be easily implemented by currently available data base packages or expert system shells. Secondly, the adjustment system has been designed in the form of a fuzzy rule based system. However, more research effort is needed to integrate these into one system. This system would provide an effective systematic framework for the generation of a complete construction program. The concept of an integrated system is shown in Fig. 7.1.

In order to integrate the subsystems into one integrated system, the following tasks are needed.

• Develop an interface facility between data base systems and an adjustment system.

- Develop an interface facility between the adjustment system and the currently available scheduling tools.
- Design user input/output utilities.

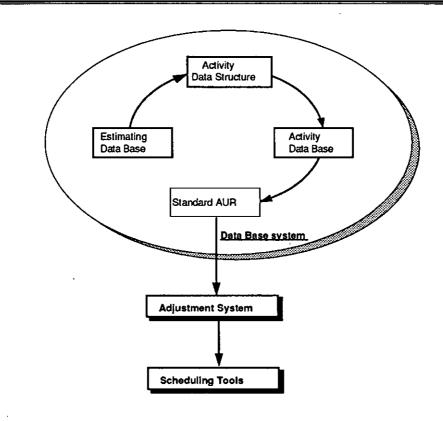


Fig. 7.1 The Concept of Integrated System

A more structured integrated system is illustrated in Fig.7.2.

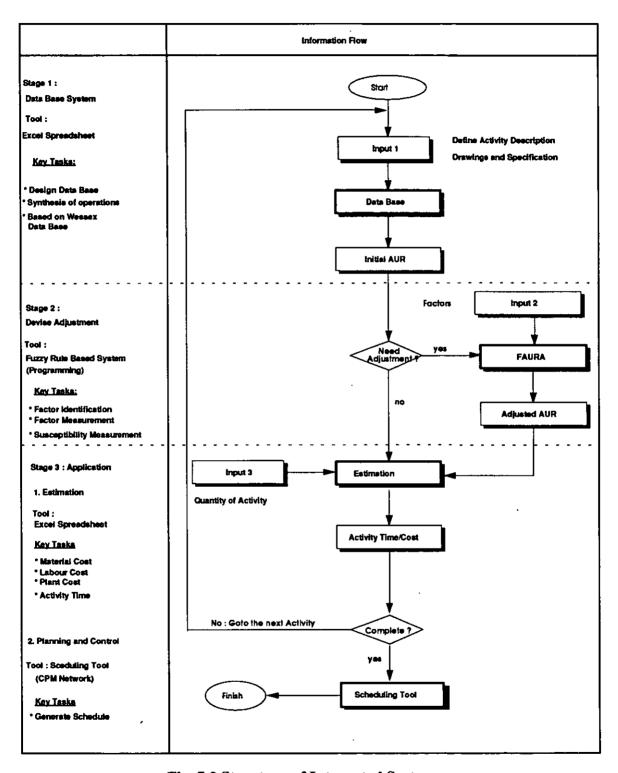


Fig. 7.2 Structure of Integrated System

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APPENDIX A: Fuzzy Weighted Average Method

A.1 FACTOR MEASUREMENT MECHANISM (FMM)

The aim of this appendix is to examine a Factor Measurement Mechanism(FFM). The fuzzy extension principle(Zadeh,1975c) and Fuzzy Weighted Average(FWA) algorithm(Dong and Wang,1985,1987) are examined since these can be used to measure the Degree of Factor(DF). The objective of the FFM is for dealing with linguistic estimation provided by users for measuring the degree of factors. The results obtained from the FFM can be used as inputs for the FAURA to deduce the AUR.

A.2 Factor Measurement Mechanism(FMM) Concept

The existence of factors can be easily identified through drawings, site visits, time of year for construction, etc.. However, measuring the existence of a factor with a certain degree is not that simple a task. For example, consider a crew skill. And we want to know whether a crew skill is good, bad or etc.. Suppose a crew experience is good, however it does not mean that a crew skill is good since the weight of importance to determine a crew skill may not be important comparing with the other criteria such as a crew morale or age. This existence of a factor with a certain degree will be referred as "Degree of Factor(DF)". Let DF denote the index value of factor i(Fi). This index value represents a degree of factor as total sum of criteria attached to them. For example, if there exists three factors, F1, F2 and F3, they can be interpretated such as F1 exists with a "very high", F2 exists with "low", and F3 exists with "medium" based on the index value of Fi through the FFM. In order to calculate the index value, each criteria must be evaluated in terms of its own rate and weight. The assignment of these values to the each criteria requires a linguistic judgement by the user since there is neither establish objective

measurment nor can we set up an experiment to measure them. Therefore, if all of the linguistic judgement could be quantified, then the overall measure of Fi could be quantified into the desired range of value. This value represents as a measure of Fi an individual factor at a particular time in a given(identified) circumstance i.e., it represents a unique project environment.

However, there is a need to establish a check list for the evaluation of all information associated with a factor. Fig.A.1 shows the possible check list format to measure a crew skill. It contains the all possible information to measure the degree of the crew skill.

Cirteria	Scale(or Ranking)	Rate	Weight
1. Morale a. Incentive b. Overtime c. Relation with Mate d. Relation with Management	0 1 2 3 4 5 6 7 8 9 10 Min Medium Max		
2. Experience	1 5 10 15 above short average good		
3. Age	20 25 30 35 40 50 above		
etc.			

Fig. A.1 Example Checklist Format

As shown in Fig. A.1., a certain criteria may requires sub-criteria list. For example, a morale has sub-criteria such as incentive, overtime, relation with mate or site managers and so on. In the case of sub-criteria measure of Ci, it will produce the rate of criteria of Ci. The list of criteria of a factor can be added or deleted depending on the level of

detail analysis required by the user. This check list format can be used as a guide to assign criteria values. Hence the user must establish an appropriate check list format as a priority. Similary, the checklist for the remain orther factors could be established.

Suppose that all necessary linguistic terms are assigned to the each criteria, then a computational model is needed to calculate the index value of a factor. The Fuzzy Weighted Average rule (Schmucker,1984, Dong and Wang, 1985,1987, Zimmermann,1986) can be applied to develop a method to measure DF. In the past, methods based on the FWA operation have been applied in civil engineering(Dong and Wang,1985, Ross,1990, Yea,1991), in particular, the structural damage assessment domain. In the following section, a formalised Factor Measurement Mechanism(FMM) is discussed.

A.3 Formulation of Factor Measurement

There exist two problems in the factor measurement which are: (1) Complexity of system, i.e., complexity of establishing factor structure due to many varied interrelated criteria of factors, and (2) vagueness associated with information due to lack of sound data and absence of clear method of measurement of criteria, i.e., measure of uncertainty associated with information. These problems must be examined before addressing the formulation of the FFM. The DF measurement strategy requires two steps:

- 1. categorising an object in a hierarchy structure(decomposition process)
- proper aggregation computation method of properties of an object (computational process)

First, a decomposition process is needed when we are dealing with vague and imprecise phenomenon. This vague concept can be structured as a hierarchy for the fuzzy information processing purposes as shown in Fig.A.2. The purpose of this decomposition process is to characterise vague concepts so that the quantification process can be followed by aggregating a given value to each property(criterion) of an object (factor) in a systematic way. As shown in Fig.B.2, each criteria requires its own rate and weight. The measurement of these values to the each criteria may not be directly(crisply) measurable, thus they can be only measured in terms of the user's(observer's) abstract images(perception) depending on the level of understanding of criteria since there is no established objective measurement nor can we set up an experiment to measure them.

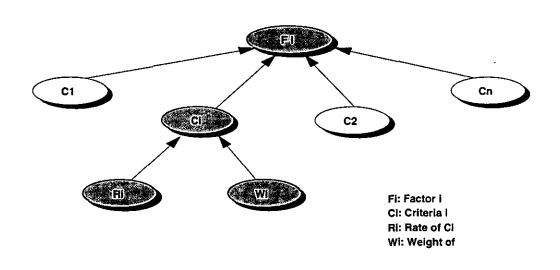


Fig. A.2 Factor Measurement Concept

Thus they can only be measured using linguistic terms which are not precise statements but are vague assertions based on the observed fact with the best available knowledge at that time. We assume that the user is capable of assigning the linguistic terms to the rate and weight of the criteria list. These two terms are described as follows:

Ri = the subjective(Fuzzy set) rate of Ci to denote the existence of a criteria with a certain degree.

Wi = the subjective(Fuzzy set) weight of Ci to Fi which expresses the relative importance of criteria among other criteria in Fi

for i= 1,2,...,n where n is the total number of criteria of Fi.

The assignment of these values uses linguistic terms as mentioned in an earlier section.

The linguistic terms could be the one of the terms such as high, low, average, very high, more or less low, extremely low(high), very good, very bad, bad, good, important, very important, less important, not important,..., etc.

The value of Ri and Wi will be estimated using linguistic term. For example, Rate is represented by the membership function $R_i = \mu_{R_i}(r_i)$. The assignment of rate value of Ci can be measured directly from its own degree based on the evidences. Similarly the weight can be assigned by the users based on their best knowledge available at that time. The weight value represented by the membership function $W_i = \mu_{W_i}(w_i)$. All fuzzy sets are assumed to be normalised(i.e. have finite support and take on the value 1 at least once).

Once all necessary fuzzy sets of weight and rate are assigned, then the next stage is to calculate the overall measure of factor i(Fi). This can be done by using EQ.1 as follows:

$$F_{i} = \frac{\sum_{i=1}^{n} R_{i} \times W_{i}}{\sum_{i=1}^{n} W_{i}} \qquad (1)$$

where the value of Fi can be interpreted as a measure degree of Fi for the activity j.

The product, Ri * Wi, in the EQ.1 is the measure of compensation or dilution between rate and weight. When all weights are equal, then EQ.1 means simply the arithmetic average. The sum of weight is equal to 1 which is the unit. EQ.1 is the method used to arrive at an overall measure of Fi. Thus if there n criteria exist, then the sum of Ci yield a relative value for the Fi of activity j when all available criteria are taken into account. EQ.1 provides a sufficient tool to perform for the factor measurement mechanism.

The origin of EQ.1 came from Kahn's probabilistic model(Kahn,1975). Bass and Kwakernaak suggest a fuzzy version of EQ.1 (Bass and Kwakernaak,1977). Since that

different authors have suggested different approach for computing the fuzzy version of Kahn's model. Among those who have studied to implement this model are Clements(1977), Dubois and Prade(1980), Nakamura(1984), Tong and Bonissone(1984), Schmucker(1984) and Dong and Wong(1985,1987). The various methods were reviewed and summarised in Zimmermann(1985).

A.4 Computational Procedures

To perform EQ.1, fuzzy algebraic operations, which is extended ordinary algebraic operations, are needed. This computational process is called 'fuzzy weighted average operations(FWA)'. To perform FWA computation by hand is a very time consuming and cumbersome process. Thus it is necessary to have an efficient and accurate algorithm which can handle this computational process in a computer implementation. The following section discusses the FWA algorithm.

a). Interval analysis and α -cuts

Each fuzzy set used in this process can be represented by interval to the corresponding α value. Fig.A.3 shows an α -cut representation of a fuzzy set.

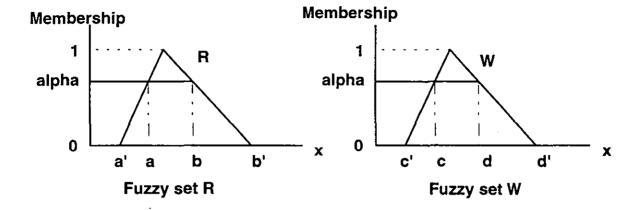


Fig. A.3 Alpha-Cut Fuzzy Sets

Let R = [a,b] and W = [c,d] denote two intervals on the real line Z, and * a binary algebraic operation as below(From):

$$R + W = [a,b] + [c,d] = [a+c,b+d]$$
(2)

$$R - W = [a,b] - [c,d] = [a-d, b-c]$$
(3)

$$R \times W = [a,b] \times [c,d] = [\min(ac,ad,bc,bd), \max(ac,ad,bc,bd)] \dots (4)$$

$$R \div W = [a,b] \div [c,d] = [a,b] \times [1/d, 1/c], 0 \notin [c,d]$$
(5)

Thus the interval algebraic operations consist of the following steps: (1) Selct a particular α -cut value, where $0 \le \alpha \le 1$. (2) Find the interval(s) in R and W which correspond to α (these are the α -cut of R and W). (3) Using interval operations, compute the interval(s) in Z which correspond to those of R and W (the results are the α -cut of Z). These steps are repeated for as many values of α as needed to refine the solution.

Example:

Consider one-term weighted average

$$F_{i} = \frac{R \times W}{W} \qquad(6)$$

Let the interval, R = [2, 5] and W = [3, 7]. For multiplication, the coresponding Z-interval in the case of , say, α =0.5, the solution is oviousely [2,5] since Fi = R. However, if we are following the EQ.6 in sequential steps, it creates some problem as shown in below:

For
$$\alpha = 0.5$$
: R × W = [2,5] × [3,7] = [\wedge (6,14,15,35), \vee (6,14,15,35)] = [2,35]
Thus DF = [2,35] ÷ [3,7] = [0.29, 11.67]

The problems of second approach is that the variable W occurs twice(one in the numerator and once in the denominator) and the two occurences are treated independently in the analysis. This creates the increasing the number of variables as three instead of two, as a result of that this has discrepancy with first result which is correct. To solve this problem, Dong and Wang(1985) introduced the combinatorial interval analysis. Followings are the combinatorial interval analysis.

Suppose the algebraic expression contains N variables as specified by

$$y = f(x_1, x_2,, x_N).$$
 (7)

Some of the variables may have multiple occurrences but they are counted only once. Suppose that $x_1, x_2,, x_N$ have the corresponding intervals $[a_1,b_1], ..., [a_n,b_n]$. The 2N end-points can be combined in 2^N distinct combinations, or permutations of an N-ary array $(x_1, x_2,, x_N)$ where x_1 can be either a_1 or b_1, x_2 can be either a_2 or b_2 , and so on. Denote these by $\beta_1, \beta_2,\beta_2^N$ where

$$\beta_1: (a_1, a_2,, a_N),$$

$$\beta_2: (b_1, a_2,, a_N),$$

$$\vdots$$

$$\beta_2^N: (b_1, b_2,, b_N),$$
(8)

The interval of y is then given by

[c,d]
$$\equiv$$
 [min{ f(β_1), f(β_2),...., f(β_2^N)}, max{ f(β_1), f(β_2),...., f(β_2^N)}]
 $=$ [$\bigwedge f(\beta_i), \bigvee f(\beta_i)$](9)

where $f(\beta_1) = f(a_1, a_2,, a_N)$, and so on.

b) Fuzzy Weighted Average(FWA) algorithm

With the combinatorial interval analysis, the FWA algorithm has following steps:

- 1. Discretize the range of membership [0,1] into finite number of values (called α_i).
- 2. For each membership value α_i , find the corresponding intervals for fuzzy sets.
- 3. Taking one end point from each of the intervals, the end points can be combined into an N-ary array. These are 2^N distinct permutations, giving 2^N combinations for the vector $(x_1, x_2,, x_N)$.
- 4. Evaluate the function $y = f(x_1, x_2,, x_N)$. The desired interval for y is given by using EQ. 9.
- 5. Repeat the process for other α 's to obtain additional α -cut of the fuzzy sets.

Dong and Wang(1985,1987) introduced this Fuzzy Weighted Average(FWA) algorithm to perform the FWA oprearion. This algorithm is an approximated computational technique. Their method makes use of the α -cut representation of fuzzy sets and interval analysis.

c) Example

Suppose, a factor i structure is established by the user as shown in Fig.B.4.

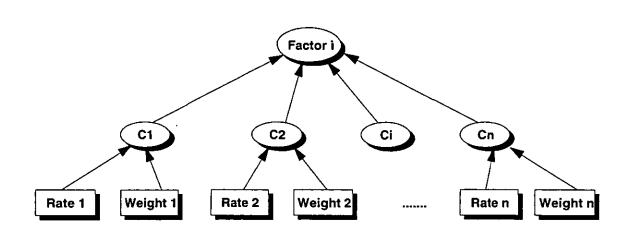


Fig. A.4 Factor Measurement Structure

Then, the overall measure of Fi can be obtained by the FWA algorithm.

Consider the Fi, called "Design Factor", and its list of criteria can be such as complexity, quality requirement, repetition etc.. To illustrate the FFM procedure, two criteria which are complexity and quality requirement are choosen for the simplicity of illustration. Form EQ.1, two-term weighted average to measure the Fi can be calculated as:

$$F_{i} = \frac{W_{1} \times R_{1} + W_{2} \times R_{2}}{W_{1} + W_{2}}$$
 (13)

where W1 and R1 are weighte and rate of C1 and W2 and R2 are weight and rate of C2 respectively as shown in Fig.B.4.

Table B.1 shows an example linguistically estimated values for the criteria from the user.

For activity j:

Factor name: Design Factor(Fi)

Criteria (Ci)	Rate(Ri)	Weight(Wj)	
C1: Complexity	Rate 1 = high	Weight 1 = very important	
C2: Quality Requirement	Rate 2 = medium	Weight 2 = less important	

Table A.1 Linguistic terms for the rate and weight

These liguistic terms can be represented by Zadeh's S and PI membrship functions as shown in Fig.A.5.

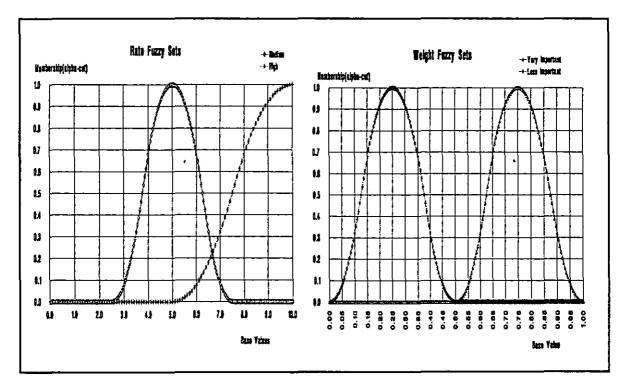


Fig. A.5 Membership Function

Then next step is the discretation process. For the refinement in the discretization of α value, 0.1 increment is given, i.e., α = 0, 0.1, 0.2, ..., 1. From Fig. B.5, the intervals of α -cut values are summarized in the table A.2.

α	Rate I	ntervals	Weight Intervals		
	Rate 1= high	Rate 2=medium	Weight 1=v.i	Weight 2 = 1.i	
0	[5, 10]	[2.5 , 7.5]	[0.5, 1]	[0, 0.5]	
0.1	[6.1, 10]	[3.05, 6.95]	[0.56 , 0.95]	[0.06, 0.45]	
0.2	[6.6 , 10]	[3.3 , 6.7]	[0.58 , 0.92]	[0.08, 0.42]	
0.3	[6.9 , 10]	[3.45 , 6.55]	[0.6, 0.91]	[0.1, 0.41]	
0.4	[7.2 , 10]	[3.6, 6.4]	[0.61 , 0.89]	[0.11, 0.39]	
0.5	[7.5, 10]	[3.75 , 6.25]	[0.63 , 0.87]	[0.13, 0.37]	
0.6	[7.8, 10]	[3.9 , 6.1]	[0.64 , 0.86]	[0.14, 0.36]	
0.7	[8.1, 10]	[4.05 , 5.95]	[0.66 , 0.85]	[0.16, 0.35]	
0.8	[8.4, 10]	[4.2, 5.8]	[0.67, 0.83]	[0.17, 0.33]	
0.9	[8.9, 10]	[4.45 , 5.56]	[0.7, 0.81]	[0.2, 0.31]	
1	[10, 10]	[5,5]	[0.75, 0.75]	[0.25 , 0.25]	

Table A.2 Intervals

For $\alpha=0$, the intervals for R1, R2, W1 and W2 are shown in Table A.3. The 2^4 permutations of the array and the corresponding values of FWA are given below.

(RI	R2 V	WI V	V2)	$F_i = \frac{W_1 \times R_1 + W_2 \times R_2}{W_1 + W_2}$	(R1 R2 W1 W2	$F_{1} = \frac{W_{1} \times R_{1} + W_{2} \times R_{2}}{W_{1} + W_{2}}$
5	2.5	0.5	0	5	5 2.5 0.5 (0.5 3.75
10	2.5	0.5	0	10	10 2.5 0.5	0.5 6.25
5	7.5	0.5	0	5	5 7.5 0.5 (0.5 4
10	7.5	0.5	0	10	10 7.5 0.5	0.5 8.75
_5	2.5	1	0	5	5 2.5 1	0.5 4.17
10	2.5	1	0	10	10 2.5 1 (0.5 7.5
5	7.5	1	0	5	5 7.5 1	0.5 5.83
10	7.5	1	0	10	10 7.5 1	0.5 9.17

Table A.4 Combination Array

The FWA values for the each combinations are:

(5, 10, 5, 10, 5, 10, 5, 10, 3.75, 6.25, 4, 8.75, 4.17, 7.5, 5.83, 9.17).

Thus the desired interval for z can be founded using EQ.9 as [3.75, 10]. This interval defines the 0-cut of the interval. The process is repeated for α =0.1, 0.2, ..., 1, but the algebra is omitted. The results are shown in Table A.5.

α	Mini	Max	α	Mini	Max
0.1	4.74	9.82	0.6	6.396	9.47
0.2	5.21	9.74	0.7	6.696	9.36
0.3	5.5	9.66	0.8	7.014	9.286
0.4	5.8	9.6	0.9	7.53	9.12
0.5	6.11	9.51	1	8.75	8.75

Table A.5 Final Interval

The final interval is plotted in Fig. A.6.

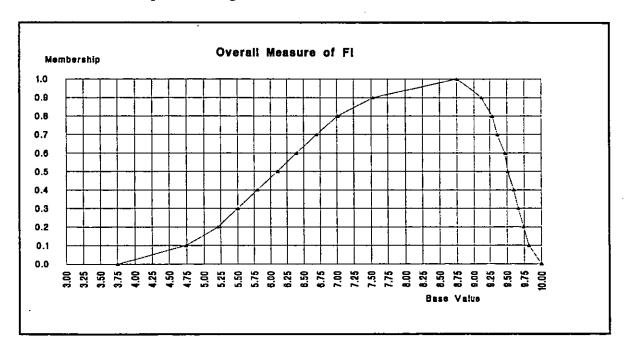


Fig. A.6 Overall Measure of Fi

A.4 FWA Output Interpretation

Once the final curve as shown in Fig.A.6, as results of the FWA algorithm, then it is necessary to have an interpretation process of this curve into the natural linguistic term. This curve can not give any meaning by itself since it contains a fuzzy concept which is neither the linguistic term nor single numerical value. Furthermore, this final curve will be used as input for the FAURA. In order to do so, it must be reinterpreted into the natural linguistic term so that the inference process can be initiated.

This curve can be interpreted by using Fuzzy Mean(FM) operation. The FM is calculated as follows:

$$FM_{i} = \frac{\sum_{i=1}^{n} \alpha_{i} \times u_{i}}{\sum_{i=1}^{n} \alpha_{i}} \qquad \dots (14)$$

For the output interpretation process to the natural linguistic term, the FM value of Fi, which is a single numerical number, is needed to compare with the predefined standard. For this reason, it is necessary to establish a unique level of standard. This predefined standard for the possible fuzzy sets can be constructed through the experiment. For example, if all criteria of Fi have very high rate and weight, then it will yield very high final curve for the Fi. In this way, it is possible to calculate the Fuzzy Mean(FM) value using EQ.14. corresponding to the very high curve. Then, the FM value becomes a standard for the very high of Fi. Thus if we could set up such standard, then it is possible to interpretate the FM value of the final curve into the natural linguistic term.

Suppose, a FM of Fi is ranged between 0 and 10. Then when the value of FMi is closed to 0, it means that Fi can be interpreted as extremely low. When the value of FMi is closed to 10, it means that Fi can be interpreted as extremely high. And, when the value of FMi is equal to any other value in the range 0 to 10 it means that Fi has some degree.

For example, a fuzzy set, B, is defined as follows:

$$B = (0.1/7, 0.3/8, 0.8/9, 1/10)$$

and then using EQ.14:

$$B = 9.23$$

Then the fuzzy set B can be interpreted as very high since The FM value of the fuzzy set, B, belong to the very high range, say, 8 to 10.

This completes Fuzzy Factor Measurement(FFM) process.

APPENDIX B: Classification System

A. CI/SfB Classification System

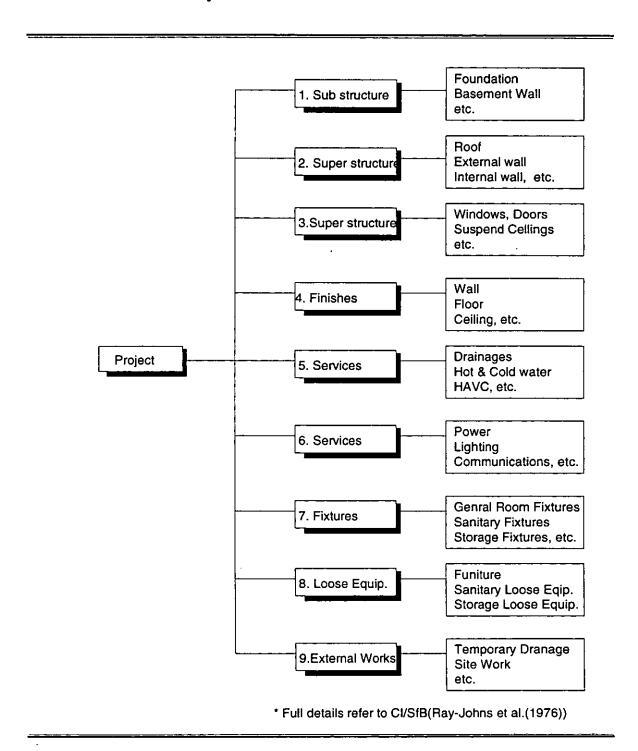


Fig. B1. CI/SfB Classification System

B. CAWS Classfication System

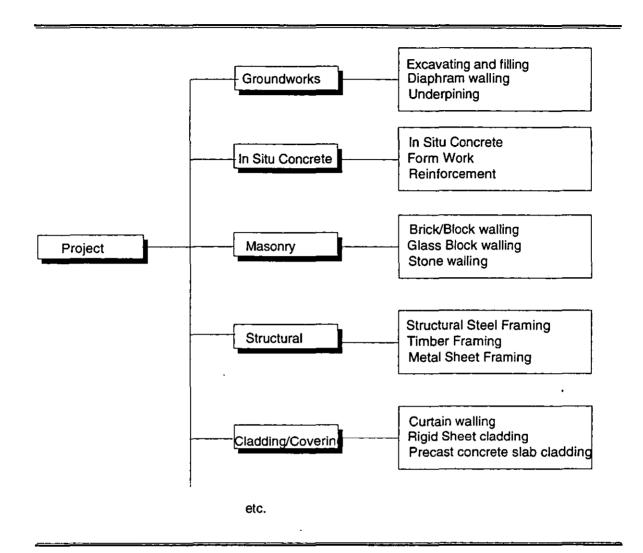


Fig. B2. CAWS Classification System

APPENDIX C: The Compatibility Measurement Method

1. Compatability Measurement

In order to calculate the compatibility(let this denote N), following equations are given by Nafarieh and Keller(1991).

where

f[comp(A*,A)] =

Let, $\mu_{ture}(x) = x$ in EQ.1. Thus, after integration of left side in EQ.1, there will be 1/(N+1). Therefore, the only unknown variable is the comp(A*,A). Hence, if we know the comp(A*,A) value, then it is possible to calculate N value which is the measure of computability. The comp(A*,A) is defined by the following equation:

$$comp(A^*, A) = \frac{|A^* \cap A|}{|A^* \cup A|} \qquad (5)$$

where A^* is an input and A is a premise of rule and \bigcap , \bigcup and $|\cdot|$ denote intersection, union and area under the fuzzy set respectively. There exist four cases to consider in order to compute the comp(A^* ,A). The followings describes these cases more detail.

Case 1: Very family.

Suppose A* is subset of A, i.e., A* is either equal to A, or more specific than $A(A^* \subseteq A)$. In this case, the N value must be greater than or equal to $1(N \ge 1)$. For example, hedges such as *very*, *very very*, *extremely*, etc. belong to this case. Thus, this case is referred as the very family and EQ.2 is designed for this (case c in Fig.D.1). As shown in Fig.C.1, the comp(A*,A) can be computed as follows:

$$|A^* \cap A|$$
 = area under A^* , or $|A^* \cup A|$ = area under A .

Hence

$$comp(A^*,A) = \left| \frac{A^* \cap A}{A^* \cup A} \right| = \left| \frac{A^*}{A} \right| \qquad (6)$$

where $|.|, \cap$ and \cup denote area, intersection and union respectively.

Case 2: More or less family

If A^* contains $A(A^* \supset A)$ i.e., then A^* considered as less specific than A(case d in Fig. C.1). In this case, the N value must be less than 1(N < 1). Hedges such as *more or less*, *very more or less*, *quite*, etc. belong to the case 2. Thus, the case 2 is referred as the more or less family and EQ.3 is designed for this. In this case, the comp (A^*,A) can be computed as follows:

$$|A^* \cap A|$$
 = area under A
 $|A^* \cup A|$ = area under A*

Hence

$$comp(A^*,A) = \left| \frac{A^* \cap A}{A^* \cup A} \right| = \left| \frac{A}{A^*} \right| \qquad (7)$$

where $|.|, \cap$ and \cup denote area, intersection and union respectively.

Case 3. Unkown

However, A* and A may be disjoint. In this case, the N value is 0. This implies that there is so little in common between A* and A. Thus the inference result B* will be unknown.

Case 4. About

If A^* is not a subset of $A(A^* \not\subset A$ and $A \not\subset A^*$) i.e., A^* and A are intersect(case b in Fig C.1). In this case, the N, can be found through approximate method and the process of $comp(A^*,A)$ computation is somewhat complicated. This type of hedges is not considered in this study.

Fig. C.1 shows these four cases. In Fig.C.1, the dotted area represents an intersection of A^* and $A(A^* \cap A)$ and the area under thick line represents a union of A^* and $A(A^* \cup A)$. To measure the degree of compatibility which is $comp(A^*,A)$, it is necessary to calculate the area of A^* and A as shown in Fig.C.1. This can be obtained by an integration operation. For this integration operation, the input fuzzy set A^* and premise fuzzy set A in a rule should be represented by the liner functions. Otherwise, the integration will be quite complicated. For this reason, the generalised linear membership function is defined in section B. Once the $comp(A^*,A)$ value is defined after integration, then it is possible to obtain the N value using EQ.1.

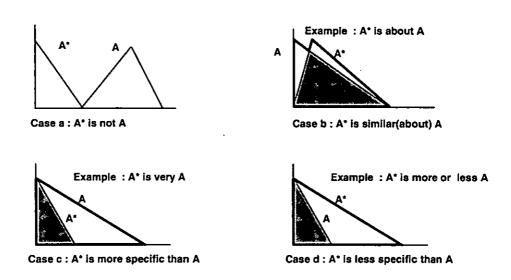


Fig. C.1 Compatibility Measurement Concept

This completes an investigation of the theoretical properties of the compatibility measurement method proposed by Nafarieh and Keller(1991).

2. Generalised Membership Functions

The linear membership function can be used to generate the input fuzzy set, A*, and primary fuzzy sets, A, in the premise of rules. The reason of using the linear membership functions is for the simplicity of calculating the compatibility measurement between a fuzzy set, A in the premise of rule and an input fuzzy set, A*. More specifically, it is very convenient to calculate the area under fuzzy sets A and A* in order to measure the compatibility. Hence, the membership function should be continuos(linear) function so that the integral calculations can be done easily.

For this purposes, the generalised fuzzy membership functions are defined as follows.

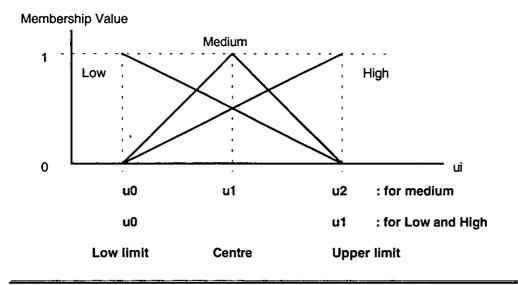


Fig. C.2 Generalised Fuzzy Membership Function

i) Low(or Bad):

$$\mu_{Low}(u) = \frac{1}{u_1 - u_0} + \frac{u_1}{u_1 - u_0} ; \quad 0 \le u \le u_0$$

$$0 ; \quad u_0 \le u \le u_1 \dots (8)$$

ii) High(or Good)

$$\mu_{High}(u) = \frac{u}{u_1 - u_0} - \frac{u_0}{u_1 - u_0} ; \quad 0 \le u \le u_0$$

$$1 ; \quad u_0 \le u \le u_1$$

$$\vdots \quad u_1 \le u$$
.....(9)

iii) Medium(or Average)

$$\mu_{Medium}(u) = \begin{array}{c} 0 & ; & 0 \le u \le u_0 \\ \frac{u}{u_1 - u_0} - \frac{u_0}{u_1 - u_0} & ; & u_0 \le u \le u_1 \\ -\frac{u}{u_2 - u_1} + \frac{u_2}{u_2 - u_1} & ; & u_1 \le u \le u_2 \\ 0 & ; & u_2 \le u \end{array}$$
(10)

Thus, using these membership functions, it is possible to generate the input fuzzy sets, A* and the primary fuzzy sets, A, in the premise of rules.

3. Example

Stage 1 Compatability Measurement

For the simplicity, the fuzzy sets are modelled as triangular fuzzy membership on U = [1,11], where good(A1) and bad(A2) in the example are defined by using the generalised membership function in EQ.8 and 9 respectively:

$$\mu_{A1}(u) = \begin{cases} \frac{1}{5}(u-5); & 5 \le u \le 10 \\ 0; & u \le 5 \end{cases}$$

$$\mu_{A_2}(u) = -\frac{1}{4}(u-5); \quad 1 \le u \le 5$$

$$0; \quad 5 \le u$$

Also, Very high(A*1) and More or Less Bad(A*2) can be defined by using Zadeh's Hedge operators as follows:

$$\mu_{A^{*}1}(u) = \begin{cases} \frac{1}{5}(u-5)]^2; & 5 \le u \le 10 \\ 0; & u \le 5 \end{cases}$$

$$\mu_{A^*_{2}}(u) = \begin{bmatrix} -\frac{1}{5}(u-5)]^{0.5}; & 0 \le u \le 5 \\ 0; & 5 \le u \end{bmatrix}$$

Case 1

Since this case is belong to the very family as shown in the case C in Fig.D.1, the area under intersection and union are:

$$|A_1 * \cap A_1| = A_1 * = \int_5^{10} (\frac{u}{5} - 1)^2 = \frac{5}{3}$$

$$|A_1 * \cup A_1| = A_1 = \int_5^{10} (\frac{u}{5} - 1) du = \frac{5}{2}$$

Hence, using EQ.6,

$$comp(A_1^*, A_1) = \left| \frac{A_1^* \cap A_1}{A_1^* \cup A_1} \right| = \frac{2}{3}$$

From EQ.2, we have

$$\int_{0}^{1} \mu_{M}(x) dx = \int_{0}^{1} (x)^{N} dx = \int_{0}^{1} x dx \times comp(A, B)$$

After integration we obtain

$$\frac{1}{N+1} = \frac{1}{2} \times \frac{2}{3}$$
 Therefore, N = 2.

Now, we can find B₁* as:

$$\mu_{B,*}(v) = [\mu_{B,}(v)]^N = [\mu_{B,}(v)]^2$$

That is $B^* = \text{very } B$ according to the Zadeh's Hedge interpretation, and this result also matches the intuitive relation suggested by the Mizumoto et al(1979)(Refer Table 5.1 in chapter 5).

Case 2:

Since this case is belong to the More or Less family as shown in the case d in Fig.D.1, the area under intersection and union are:

$$|A_2 * \cap A_2| = A_2 = \int_1^5 -\frac{1}{4}(u-5)du = 2$$
$$|A_2 * \cup A_2| = A_2^* = \int_1^5 [-\frac{1}{4}(u-5)]^{0.5} du = \frac{8}{3}$$

Hence, using EQ.7,

$$comp(A_2^*, A_2) = \left| \frac{A_2^* \cap A_2}{A_2^* \cup A_2} \right| = \frac{3}{4}$$

From EQ.3, we have

$$\int_{0}^{1} \mu_{M}(x) dx = \int_{0}^{1} (x)^{N} dx = \int_{0}^{1} x dx \div comp(A_{2}^{*}, A_{2})$$

After integration we obtain

$$\frac{1}{N+1} = \frac{1}{2} \div \frac{3}{4}$$
 Therefore, N = 0.5

Hence, we can find B2* as

$$\mu_{B_1^*}(v) = [\mu_{B_2}(v)]^{0.5}.$$

That is B_2^* = More or Less B_2 according to the Zadeh's Hedge interpretation, and this result also matches the intuitive relation.

APPENDIX D: Curve.C Computer Program List

```
*************
        FILE NAME: CURVE.C
         FUZZY STANDARD MEMBERSHIP FUNCTION GRAPH
/* This program is written to generate the required fuzzy sets for the
Activity Unit Rate and Evidence list. The output of this operation will be
stored into SP(prolog) subdirectory, so that the main program can be retrived
the necessary data files conviently. To operate this program,
Type PROGRAM FILE NAME and give FILE_NAME and hit return key, eq. CURVE high,out.
#include<stdio.h>
#include<math.h>
#include<alloc.h>
#define ABS(x) ((x)<0 ? -(x):(x))
main(int argc, char **argv)
int i,n1=0,n2=0,n3=0,ans,range;
/* */
double k:
float alfa1, beta1, gama1, alfa2, beta2, gama2, alfa3, beta3, gama3;
float ss[110], p[110], sm[110], temp;
float sl,su,ml,mu,ll,lu; /*fuzzy set base range(low and upper limit) */
FILE *fp, *fopen();
       if(argc < 2){
       printf("type: curve file_name.out\n");
       exit(0);
       INPUT SCREEN
printf("\nTHIS PROGRAM IS WRITTEN FOR GENERATING FUZZY SET
MEMBERSHIP VALUE.");
    printf("\n\n\t[If you want to quite program: enter control+C:]");
       printf("\n\n\tPlease Select One that you want to generate a fuzzy set:");
       printf("\n\n\t 1 for LOW");
       printf("\n\n\t 2 for MEDIUM");
       printf("\n\n\t 3 for HIGH\n\t"); scanf("%d",&ans);
       printf("\tYou have choosen %d fuzzy set\n",ans);
```

```
printf("\nTHIS PART IS FOR ASKING TOTAL NO. OF POINTS IN A X AXIS(BASE
VALUE).");
       printf("\n\n\tPlease input the number of points for the base range:\t");
       scanf("%d",&range);
       printf("\tNumber of points in the base value range is :%d\n",range);
        SS CURVE : SMALL or LOW
if(ans==1){
    printf("\nTHIS PART IS FOR ASKING LOW AND UPPER LIMMIT OF BASE RANGE ");
       printf("\n\n\tDefine [Start point of low limmit] sl\n\t");
       scanf("%f", &sl);
       printf("\t Low limit point of LOW FUZZY SET is ::%f\n",sl);
       printf("\n\n\tDefine [End point of upper limmit] su\n\t");
       scanf("%f",&su);
       printf("\t Upper limit point of LOW FUZZY SET is ::%f\n",su);
    printf("\nTHIS PART IS FOR ASKING ALPHA,BETA AND GAMMA PONIT IN THE
BASE RANGE ");
       printf("\n\n\tInput ALPHA : [STARTING POINT]\n\t");
       scanf("%f",&alfa1);
       printf("\t ALPHA of LOW FUZZY SET is ::%3.3f\n",alfa1);
       printf("\n\n\tlnput BETA: [CENTRE POINT]\n\t");
       scanf("%f",&beta1);
       printf("\t BETA of LOW FUZZY SET is ::%3.3f\n",beta1);
       printf("\n\n\tInput GAMMA : [END POINT]\n\t");
       scanf("%f",&gama1);
       printf("\t GAMMA of LOW FUZZY SET is ::%3.3f\n",gama1);
       printf("\n\sl=\%3.3f su=\%3.3f\n",sl,su);
       printf("alfa1=%3.3f beta1=%3.3f gama1=%3.3f\n",alfa1,beta1,gama1);
       for(i=sl*range; i <= su*range; i++){
       k=(double)i/range;
       n1++;
       if(k \le alfa1){
                ss[i]=1.0;
       }
       else
       if ( k>alfa1 && k<= beta1){
               temp=(k-alfa1)/(gama1-alfa1);
```

```
ss[i]=1 - 2 * (pow(temp,2));
       }
       else
       if (k > beta1 && k <= gama1){
               temp=(k-gama1)/(gama1-alfa1);
               ss[i]= 2*(pow(temp,2));
       }
       else
       if(k >= gama1){
               ss[i]=0.0;
printf("data(%3.2f,%3.2f)\n",k,ss[i]);
  } .
}
 else
          PI.CURVE: MEDIUM
if(ans==2){
       printf("\nTHIS PART IS FOR ASKING LOW AND UPPER LIMMIT OF BASE RANGE ");
       printf("\n\n\tDefine [Start point of low limmit] ml\n\t");
       scanf("%f", &ml);
       printf("\t Low limit point of MEDIUM FUZZY SET is ::%f\n",ml);
       printf("\n\n\tDefine [End point of upper limmit] mu\n\t");
       scanf("%f",&mu);
       printf("\t Upper limit point of MEDIUM FUZZY SET is ::%f\n",mu);
       printf("\nTHIS PART IS FOR ASKING BETA AND GAMMA PONIT IN THE BASE
RANGE ");
       printf("\n\n\tFor the Medium, only BETA and GAMA are required for input\n");
       printf("\n\n\tlnput BETA :: [BAND WEITH from centre point] for MEDIUM range\t");
       scanf("%f",&beta2);
    printf("\t BETA of MEDIUM FUZZY SET is ::%3.3f\n",beta2);
        printf("\n\n\tlnput GAMMA : [CENTRE POINT]\n\t");
        scanf("%f",&gama2);
       printf("\t GAMMA of MEDIUM FUZZY SET is ::%3.3f\n",gama2);
        printf("beta2=%f gama2=%f\n",beta2,gama2);
       for(i=ml*range; i < mu*range+1; i++){
     k=(double)i/range;
       n2++;
        alfa2=gama2-beta2;
        if(k <= gama2-beta2){
```

```
p[i]=0.0;
        }
        else
        if(k > gama2-beta2 && k <= (gama2-beta2/2)){
        p[i]= 2 * pow((k-alfa2)/(gama2-alfa2),2);
        }
        else
        if(k > (gama2-beta2/2) && k <= gama2){
                p[i]= 1 - 2*(pow((k-gama2)/(gama2-alfa2),2));
        else
        alfa2=gama2+beta2;
        if(k > gama2 && k <= gama2+beta2/2 ){
                p[i]= 1-2 * pow( (k-gama2)/(gama2-alfa2) ,2);
        }
     else
        if(k > gama2+beta2/2 \&\& k <= gama2+beta2){
                p[i]= 2 * pow( (k-alfa2)/(gama2-alfa2) ,2) ;
        }
      else
        if(k > gama2+beta2 ){
                p[i] = 0.0;
printf("data(%3.2f,%3.2f)\n",k,p[i]);
}
else
                SL.CURVE: LARGE OR HIGH
if(ans==3){
        printf("\nTHIS PART IS FOR ASKING LOW AND UPPER LIMMIT OF BASE RANGE ");
        printf("\n\n\tDefine [Start point of low limmit] I\n\t");
        scanf("%f", &II);
        printf("\t Low limit point of HIGH FUZZY SET is ::%f\n",II);
        printf("\n\n\tDefine [End point of upper limmit] lu\n\t");
```

```
scanf("%f",&lu);
       printf("\t Upper limit point of HIGH FUZZY SET is ::%f\n",lu);
    printf("\nTHIS PART IS FOR ASKING ALPHA,BETA AND GAMMA PONIT IN THE
BASE RANGE "):
       printf("\n\n\tlnput ALPHA : [STARTING POINT]\n\t");
       scanf("%f",&alfa3);
       printf("\t ALPHA of HIGH FUZZY SET is ::%3.3f\n",alfa3);
       printf("\n\n\tInput BETA : [CENTRE POINT]\n\t");
       scanf("%f",&beta3);
       printf("\t BETA of HIGH FUZZY SET is ::%3.3f\n",beta3);
       printf("\n\n\tlnput GAMMA : [END POINT]\n\t");
       scanf("%f",&gama3);
       printf("\t GAMMA of HIGH FUZZY SET is ::%3.3f\n",gama3);
       printf("alfa3=%f beta3=%f gama3=%f\n",alfa3,beta3,gama3);
       for(i=ll*range; i < lu*range+1; i++){
    k=(double)i/range;
       n3++;
       if(k \le alfa3){
                sm[i]=0.0;
       }
       else
       if ( k>alfa3 && k<= beta3){
               temp=(k-alfa3)/ (gama3-alfa3);
               sm[i]= 2 * (pow(temp,2));
       }
       else
       if ( k > beta3 && k <= gama3){
              temp=(k-gama3)/(gama3-alfa3);
               sm[i] = 1 - 2*(pow(temp,2));
       }
       else
       if(k \ge gama3)
              sm[i]=1.0;
printf("data(%3.2f,%3.2f)\n",k,sm[i]);
```

else

```
printf("INCORRECT INPUT !! TRY AGAIN\n");
        goto begin;
        DATA OUTPUT
        fp = fopen(argv[1],"w");
        printf("\n\tPRESS ANY KEY FOR OUTPUT\n");
        getch();
        printf("\n");
printf("s!=%f su=%f ml=%f mu=%f ll=%f lu=%f\n",sl,su,ml,mu,ll,lu);
printf("n1=%d n2=%d n3=%d\n",n1,n2,n3);
        printf("\n");
        fprintf(fp,"%d\n",n1);
        fprintf(fp, "%d\n", n2);
        fprintf(fp,"%d\n",n3);
*/
        if(ans==1){
         for(i=sl*range; i< su*range; i++){
         k=(double)i/range;
         printf(" %3.3f\n\t",k);
         fprintf(fp,"%3.3f\t",k);
         printf(" %3.3f\n", ss[i]);
         fprintf(fp,"%3.3f\n",ss[i]);
        }
    }
     if(ans==2){
         for(i=ml*range; i< mu*range+1; i++){
         k=(double)i/range;
         printf(" %3.3f\n\t",k);
         fprintf(fp, "%3.3f\t", k);
         printf(" %3.3f\n", p[i]);
         fprintf(fp, "%3.3f\n", p[i]);
        }
}
         if(ans==3){
         for(i=II*range; i< Iu*range+1; i++){
         k=(double)i/range;
         printf(" %3.3f\n\t",k);
         fprintf(fp,"%3.3f\t",k);
         printf(" %3.3f\n", sm[i]);
```

APPENDIX E: FAURA Computer Program List

1 Computer Implementation of the FAURA

A rule based system proposed in this study is a computerised fuzzy reasoning system to predict the most likely activity time and cost under given set of factor influence. This section describes how the FAURA can be structured into computer programs. This program will geenrate the output(predicted AUR, activity time and cost) based on the user input value of Fi via an inference strategy. The flow chart of this program is shown in Fig. F.1 which consists of 4 blocks. The arrows that enter and exist in a main clause structure indicate the flow of data. When an arrow enters a main clause, it means that the value of data is passed to the series of sub clauses attached to the main clause. All data generated during this process is located in the output position in the main clause.

In this section, the key clauses in each blocks are explained.

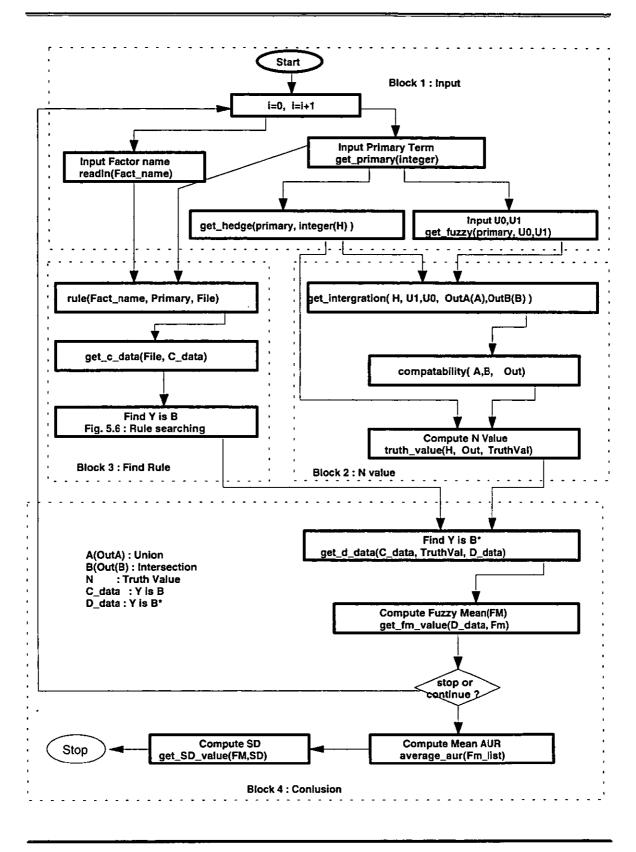


Fig.E.1 Flowchart

1. User Input Module

The main purpose of these inputs are to find fuzzy set Bi(data file) from the rule base so that the N value can be applied to the B in order to get B*. To achive this objective, three input queries are designed which are: (1) selection of factor name(Fi), (2) selection of primary term for Fi, and (3) selection of the hedge of the primary term. For example, if Fi is measured as *very high* by user. Then, user must separate them into primary term input, *high* and hedges *very*. The input quires are designed on computer screen for this purposes, thus user simply selects the choices on the screen to the corresponding primary term and hedges of Fi. Then the primary input is passed to the block 2 for the searching rule and the hedges input is passed to the block 3 for the N value calculation.

2. Block 3: Rule Seraching

Once the rules are stored in the data base of the Turbo Prolog program, then rule searching strategy is needed to retrieve the Bi. In order to find a Bi which is saved as file under DOS sub-directory, it requires user input as explained previous section. Thus, if a user inputs factors mane and primary term, then these are passed to the rule base in the block 3. To implement this process, the series of clauses are needed. This is shown in Fig.F.2 If data file is empty or failure to find it, then an error message will be appeared on the computer screen.

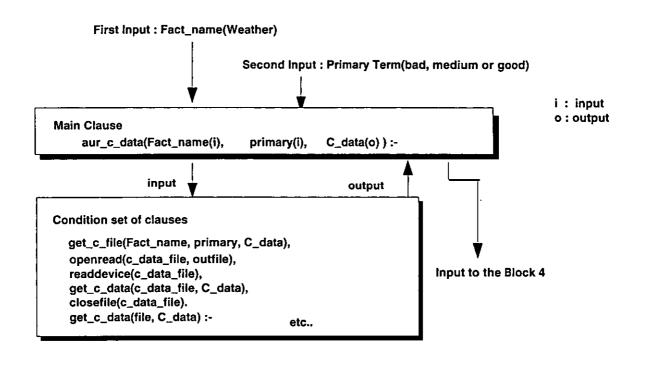


Fig.E.2 Rule searching

Once the Bi is find, the this is pass to the block 4 inoreder to define B* which is the deduced fuzzy set for the AURj.

3. Block 2: Inference Module

This process is begin with generating T-norm fuzzy set(T-fuzzy set) so that the compatability value(N value) can be calculate. In order to generate T-fuzzy set for the A and A*, it requires to input U0 and U1 values which are the low limit and upper limit of A fuzzy set(T-fuzzy set). Then using generalised T-fuzzy set membership function defined in Appendix C, the fuzzy set for the A and A* can be defined. Once these two fuzzy set are defined, then the compatability can be measured depending on the hedge type. This process involves the intergration operation in order to calculate area of union and intersection.

Once the hedge inputs are passed to the Block 2, then the compatibility measurement process is started. The Block 2 is to calculate N value. To do this, the several key clauses are shown in Fig.F.1. The first clause in block 2 having the form 'get_intergation(Interger,U0,U1,OutA,OutB):-' is designed to calculate the union and intersection. The Integer, OutA and OutB stand for hedge selection number, the union and intersection respectively. The syntax ':-' represent IF condition in the clause. Thus, the OutA and OutB can be defined only if the following definitions are exist(This is for the hedge selection, number 2, case only). After intergration of generalised linear membership function for the high and very high, the following result can be defined:

OutA =
$$(U1-U0)/2$$
,
OutB = $(U1-U0)/3$.

Then these values are passed to the second clauses having the following form:

Out = B/A.

where A, B and Out stand for union, intersection and compatibility value respectively.

This value is then input to the next clause having the following form:

where _ represents any number in the very family hedges such as very , very very, etc.; and Comp is the value of compatibility measure; and TruthVal is the N value. Finally this N value is ready to use for the Block 4.

4. Blobk 4: Output Treatment

The outputs from both block 2 and 3 are then passed to the block 4. The purpose of block 4 is to find d_data which is a conclusion 'Y is B*'. To find this, the clause 'get_d_data(c_data, N, d_data)' is written. Once d_data is calculated, Then this is passed to the next clause to calculate the fuzzy mean value(FM). This FM value is for the one output from one factor. Thus if there exist 5 factors, then it requires to run same process for five times.

5. Computer Program List

get_integration(integer,realvalue,realvalue,realvalue)

```
factor(4, weather).
factor(5,crew).
/* Expert rules : If X is B Then Y is C. */
/* Factor -- F1=Design(Des) */
rule(design.bad."desh4.dat").
rule(design,medium,"desm.dat").
rule(design,good,"desl4.dat").
/* Factor -- F2=Management Control(MC) */
rule(management,bad,"mch4.dat").
rule(management, medium, "mcm.dat").
rule(management,good,"mcl4.dat").
/* Factor -- F3=Weather */
rule(weather,bad,"weah4.dat").
rule(weather, medium, "weam.dat").
rule(weather,good,"weal4.dat").
/* Factor -- F4=Crew related */
rule(crew,bad,"crewh4.dat").
rule(crew,medium,"crewm.dat").
rule(crew,good, "crewl4.dat").
/* Factor -- F5=Site Condition */
rule(site,bad,"siteh4.dat").
rule(site,medium,"sitem.dat").
rule(site,good,"sitel4.dat").
This part is on screen input query form.
get_factor(Factor):-
       write("Select Factor i for the analysis:\n\n"),
       write("1===> Design Factor\n"),
       write("2===> Management of Control\n"),
       write("3===> Weather\n4===> Crew\n5===> Site Condition\n"),
       write("Enter Your Choice: "),
       readint(P),
       member(P,[1,2,3,4,5]),
       factor(P,Factor).
get_factor(Factor):-
       write("invalidate input, try again!\n"),
       get_factor(Factor).
get_fuzzy_set(P):-
               write("please estimate Factor i(Fi) and Select the class of Fi::\n\n"),
       write("1 ===> bad\n2 ===> medium\n3 ====> good\n\n"),
       readint(P),
       member(P,[1,2,3]).
```

```
get_fuzzy_set(P):-
        write("invalidate input, try again!\n"),
        get_fuzzy_set(P).
member(X,[XI_]).
member(X,[_IRest]):-
        member(X.Rest).
primary(1,bad).
primary(2,medium).
primary(3,good).
hedge(1,"same as").
hedge(2,"very").
hedge(3,"very very").
hedge(4,"extreamly").
hedge(5,"more or less").
hedge(6,"very more or less").
hedge(7,"about").
*/
get_boundary_input(P,U0,U1):-
        write("input U0(low limmit value of",P," fuzzy set):\n"),
        readreal(U0),
        write("input U1(upper limmit value of",P," fuzzy set:\n"),
        readreal(U1).
get_operation(B,O):-
        write("Select the nearest linguistic term of Fi !:\n\n"),
        write("1 --->Fi = same as ",B, "\n2 ---> very ",B, "\n3 ---> very very ",B.
        "\n4 ---> extreamly ",B,"\n5 ---> more or less ",B,"\n"),
        readint(O).
        member(O,[1,2,3,4,5]).
get_operation(X,Y):-
        write("invalidate input, try again!\n"),
        get_operation(X,Y).
/******************************
This part is for the union and intersection operation using intergration
operation.
get_integration(primary,Operation,U0,U1,OutA,OutB)
Out A and OutB stands for union and intersection respectively.
get_integration(1, __, _, 2, 1).
get_integration(2,U0,U1,OutA,OutB):-
        OutA=(U1-U0)/2,
        OutB=(U1-U0)/3.
get_integration(3,U0,U1,OutA,OutB):- /** very very **/
        OutA=(U1-U0)/2,
        OutB=(U1-U0)/5.
get_integration(4,U0,U1,OutA,OutB):-
        OutA=(U1-U0)/2,
```

```
OutB=(U1-U0)/9.
get_integration(5,U0,U1,OutA,OutB):-
       OutB=(U1-U0)/2,
       OutA=(U1-U0)/1.5.
get_integration(6,U0,U1,OutA,OutB):-
       OutB=(U1-U0)/2,
       OutA=(U1-U0)/1.25.
get_integration(7,U0,U1,OutA,OutB):-
       OutA=(U1-U0)/2,
       OutB=0.
*/
  ***********************
This part is for compatability and truth value N.
compatability(A,B,Out):-
       Out=B/A.
truth_value(1,Comp,TruthVai):-
       TruthVal =Comp+0.5.
truth_value(5,Comp,TruthVai):-
       TruthVal = 2*Comp-1.
truth_value(6,Comp,TruthVal):-
       TruthVal = 2*Comp-1.
truth_value(_,Comp,TruthVal):-
       TruthVal=2/Comp-1.
This part is to open and read C_data file which was generated by standard
function sub routine program written by C and get a set of C_data in [] form.
get_c_data(File,C_data):-
       not(eof(File)),
       readterm(xy_data,data(X,Y)),
       get_c_data(File,C_data1),
       C_data=[data(X,Y)|C_data1].
get_c_data(_,[]):-
aur_c_data(Fact_name,Primary,C_data):-
       rule(Fact_name, Primary, Out_file),
       openread(c_data_file,Out_file),
       readdevice(c_data_file),
       get_c_data(c_data_file,C_data),
       closefile(c_data_file).
aur_c_data(_,_,[]):-
               /.-
*********\በ"),
       write("Something wrong with C_data file !! Check C_data file!!\n\n").
This part is to calculate D_data set in data(X,Y1) form using power of N
operation over C_data.
Y1 is the Yi of D_data set. X is Xi value of C_data set.
```

```
get_d_data([],_,[]).
get_d_data([data(_,0)|Rest],TrueVal,D_data):-
       get_d_data(Rest,TrueVal,D_data).
get_d_data([data(X,Y)|Rest],TrueVal,D_data):-
       Y1 = round(exp(TrueVal*ln(Y))*1000)/1000,
       get_d_data(Rest,TrueVal,D_data1),
       D_{data} = [data(X,Y1)|D_{data1}].
write_xy_list([]):-
write_xy_list([XIR]):-
       write(X," "),
       write_xy_list(R).
This part is the defuzzification process to calculate Fm value.
get_xy_sum([],0).
get_xy_sum([data(X1,Y1)|Rest],Fm):-
       get_xy_sum(Rest,Fm1),
       Fm = X1*Y1 + Fm1.
get_y_sum([],0).
get_y_sum([data(_,Y1)|Rest],Sum):-
       get_y_sum(Rest,Sum1),
       Sum = Y1+Sum1.
get_fm_value(D_data,Fm):-
       get_xy_sum(D_data,Xy_sum),
       write("xy sum is :",Xy_sum,"\n"),
       get_y_sum(D_data,Y_sum),
       write("y sum is :",Y_sum,"\n"),
       Fm = round((Xy_sum/Y_sum)*1000)/1000.
This part is for the on screen output format
inference_process(Fm) stands for
inference_process(Fact_name,Fm,Primary,O):-
       get_fuzzy_set(Primary),
       primary(Primary,P),
       get_boundary_input(P,U0,U1),
       U0 = 1, U1 = 3,
       get_operation(P,O),
       get_integration(O,U0,U1,OutValueA,OutvalueB),
       write(" Union, Output A ::", OutValueA,"\n"),
       write(" Intersection, Output B :: ", OutValueB, "\n"),
       compatability(OutValueA,OutValueB,Comp),
       write("compatability is ::", Comp,"\n"),
       truth_value(O,Comp,TruVal),
       write("truth value N is ::",TruVal,"\n"),
```

```
aur_c_data(Fact_name,P,C_data),
      write("get C data:","\n\n["),
      write_xy_list(C_data),
      write("]\n"),
      get_d_data(C_data,TruVal,D_data),
      write("get D data:","\n\n["),
      write_xy_list(D_data),
      write("]\n"),
      get_fm_value(D_data,Fm).
This part is to calculate one output by one factor.
output_fm_value is for storing output in the list form.
get_fm_sum([],0,0).
get_fm_sum([data(_,_,,First)|Rest],Sum,Num):-
      get_fm_sum(Rest,Sum1,Num1),
      Sum = First + Sum1,
      Num = Num1 +1.
output fm_values([]).
output_fm_values([data(Name,P,O,Value)|Rest]):-
      output_fm_values(Rest),
      primary(P,Pp),
      write("IF ",Name," IS ",Oo," ",Pp," THEN AUR WILL BE",": ",Value,"\n").
This part is to calculate average output by N factor.
get_sd_sum(0,0,[],_).
get_sd_sum(Sd_sum,N,[data(_,_,_,Value)|Rest],Average):-
      get_sd_sum(Sd_sum1,N1,Rest,Average),
      Sd_sum=(Value-Average)*(Value-Average) + Sd_sum1,
      N = N1 + 1.
get_sd_value(Sd_value,Fm_list,Average):-
      get_sd_sum(Sd_sum,N,Fm_list,Average),
      Sd_value = round(sqrt(Sd_sum/(N-1))*1000)/1000.
continue_or_stop(yes,Fm_list,_):-
      main_pro(Fm_list).
continue_or_stop(_,Fm_list,Average):-
      get_fm_sum(Fm_list,Sum,Num),
      Average = round((Sum/Num)*1000)/1000,
      write("******
      output_fm_values(Fm_list),
      write("Adjusted AUR(Average) is: ", Average, "\n"),
      get_sd_value(Sd_value,Fm_list,Average),
      write("******
get_estimate(no,_).
```

```
get_estimate(yes,Average):-
      write("THIS PART IS FOR THE ACTIVITY TIME AND COST ESTIMATION.\n"),
      write("Enter Standard AUR (SAUR) of Activityj :\n\tSAUR: "),
      readreal(SAUR),
      write("Enter Activity| Quantity:\n\tQuantity: "),
      readreal(Q),
      write("Enter Activityj Crew Wages:\n\tWages: "),
      readreal(W),
      write("Enter Activityj Material Cost:\n\tMaterial Cost: "),
      readreal(M),
      write("Enter Activityj Equipment Cost:\n\tEquipment Cost: "),
      readreal(E),
      write("**************\n").
      write("The Activity duration and Cost Estimation Summary\n"),
      ND = SAUR*Q,
      write("Normal Activity Duration(Total MH) is:\n\tNormal Duration(TMH): ",ND,"MH","\n"),
      NCOST = SAUR*Q*W+M+E.
      write("Normal Ativity; Cost is:\n\tNormal Activity Cost: ","œ",NCOST,"\n"),
      write("******
      AD = Average*Q,
      write("Adjusted Activity j Duration is:\n\tAdjusted Activity Duration: ",AD,"MH","\n"),
      ACOST = Average*Q*W+M+E,
      write("Adjusted Activity) Cost is:\n\tAdjusted Activity Cost: ","œ",ACOST,"\n"),
      DCOST = ACOST-NCOST,
      write("The different Cost between Normal and Adjusted one is :\n\tThe different Cost:
","œ",DCOST,"\n"),
      DD = AD-ND,
      write("The different Duration between Normal and Adjusted one is :\n\tThe different
duration: ",DD,"MH","\n\n"),
      exit.
This part is a final loop to go to the next factor analysis.
main_pro(L) stands for main program.
main_pro(L):-
      write("*************\n").
      write("THIS PROGRAM IS DESIGNED FOR THE UNCERTAINTY FACTOR
QUANTIFICATION\n"),
      write("FOR THE AUR ADJUSTMNET PURPOSE UTILISING FUZZY SET THEORY.\n"),
      write(" Please read instruction and select answer:\n"),
      write("1
      write("Type Activity Name:\nActivity Name: "),
      readIn(Acti_name), */
      get_factor(Fact_name),
      inference_process(Fact_name,Fm,P,O),
write("*******\n"),
```

```
write("AUR under ",Fact_name," infulence is : ",Fm,"\n\n"),
write("Do you want to continue? (yes or no)\n\n"),
readln(Yes_or_No),
continue_or_stop(Yes_or_No,[data(Fact_name,P,O,Fm)IL],Average),
write("Do you want to estimate activity time and cost ?(yes or no)\n"),
readln(Yes_No),
get_estimate(Yes_No,Average).

openwrite(results_file,"output.out") ,*/
main_pro([]),
closefile(results_file).
!.
```

goal /*

*/

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