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Material design in steel making utilising mathematical modelling, knowledge-based and fuzzy logic approaches

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MATERIAL DESIGN IN STEEL MAKING UTILISING MATHEMATICAL MODELLING, KNOWLEDGE-BASED AND FUZZY LOGIC APPROACHES

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ABSTRACT

Development of knowledge-based system for material design is a complex task, due to the interrelationship of many factors in steel making process. In addition to this, design specifications vary frequently and material design knowledge is held in largely intuitive undefined format. This thesis discusses a material design system which deals with the determination of the steelmaking aim chemistry. If an attempt is made to design aim chemistry only based on a mathematical approach of utilising the empirical models between various design parameters, it would result in unrealistic design because relationships between various design parameters are not always linear. Therefore it is inevitable to apply knowledge-based methods along with the mathematical approach to deal with this complex task. The approach put forward in this thesis is a hybrid approach, where the knowledge-base is applied at every stage of the design process to utilise the expert as well as the heuristic knowledge of metallurgists to obtain the designs which are realistic and which take into account various limitations and constraints encountered in steel making. The material design is also characterised by extensive utilisation of the grade history database which contains performance data for various steel grades and thickness combinations. The inputs to the system are through interactive dialogue sessions and the inputs consist of the material standards, size, quantity, tonnage, end use and the customer special requirements. These inputs along with the numerous rules in the knowledge-bases as well as the mathematical modelling enable the effective design of the steelmaking aim chemistry.

Knowledge Elicitation (KEL) is the most important stage, but it is often the principal bottleneck in the development of knowledge-based systems. Due to the difficulties faced

in the knowledge elicitation process, development of a knowledge-based system for material design in steel making industry is a complex task. An attempt is made in this thesis to present a novel approach to deal with knowledge elicitation for material design problems in steel making industry. This research centres around the human aspects and is based on practical experience gained while developing a knowledge-based system for material design at BHP Steel, Australia. This approach involves codification of the customer special requirements to identify the knowledge sources involved in the design process. This is followed by the use of paper models to improve the efficiency of KEL process. The second stage of the structured interviews is based on the customer special requirement codes for eliciting the missing information and for clarifying any ambiguities or inconsistencies. This research also focuses on the use of non-interviewing techniques to elicit the expert knowledge in order to reduce the expensive interview time. The knowledge representation scheme developed for the material design system aims at reducing the search time and storage space by utilising the codification scheme to classify various knowledge sources into appropriate categories.

The thesis then presents the application of fuzzy logic to the material design system to rank the alternative steel making aim chemistries according to the degree which will satisfy the customer's requirements of chemistry and mechanical properties, with due consideration given to the economic aspects and the complexity involved in the production. Statistical data regarding the performance of the grades produced in the past are also utilised in this process. The development of the membership functions for the material design fuzzy logic based system, which is an important task, is presented in this thesis. Four factors considered in the development of the membership functions include chemistry, mechanical properties, relative cost and the complexity involved in the production of the steel material.

Finally the thesis presents the development of an interactive graphical user interface for a material design knowledge-based system based on a three character alphanumeric codification scheme for customer special requirements. This user interface makes the material design system more user friendly and enables error free and fast input of the basic information and the customer special requirements, corresponding to any customer order for steel plates. This is achieved through two interactive dialogue sessions utilising two input screens. In addition to making the system more user friendly and visually appealing, the interface developed also adds flexibility and sophistication to the prototype knowledge-based system for designing steel plates.

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NOMENCLATURE

X	Collection of objects (points) denoted generically by x
A, B	Fuzzy Sets in X
$\mu_A(x)$	Grade of membership of x in A
G, C, D	Fuzzy goal, constraint and decision
$\alpha_1, \alpha_2, \alpha_3$	Weighting coefficients to determine the weighted sum membership function.
X_i	ith property of the steel grade or the major code corresponding to the knowledge source.
i	i = 1, 2, ...L represents L properties of the steel grade such as tensile strength, yield strength, elongation, etc.
Y_j	jth type of steel or the sub group code for the knowledge sources.
j	j = 1, 2, ...M represents M types of steel such as structural steel, pressure vessel steel, line pipe steel, etc.
Z_k	kth value of the ith property and jth type of steel or the value code corresponding to the major and sub group code.
k	k = 1, 2, ...N represents N actual values of the properties relating to each combination of X_i and Y_j.
CSRC	Customer special requirement code
CEQ	Carbon equivalent
KB I	Tableaux rule base having chemistry and mechanical property details corresponding to material standards.
KB II	Tableaux rule base having expert knowledge required in determining chemistry corresponding to CSRCs.

KB III	Tableaux rule base having heuristic knowledge rules about end use and steelmaking aim chemistry.
KB IV	Tableaux rule base having heuristic knowledge rules to determine steelmaking aim chemistry.
CTS	Computed tensile strength.
CYS	Computed yield strength.
RTS	Required tensile strength.
RYS	Required yield strength.
TS	Tensile strength.
UYS	Upper yield strength.
RAZ	Reduction in Area in Z direction.
CLIM	Certification Limit
C	Carbon
Mn	Manganese
Si	Silicon
S	Sulphur
P	Phosphorus
Ni	Nickel
Cr	Chromium
Mo	Molybdenum
Cu	Copper
Al	Aluminium
N	Nitrogen
Ti	Titanium
Nb	Niobium
V	Vanadium

B	Boron
Ca	Calcium
A1	Critical caster alignment code
E4	Electro-magnetic stirring code
H	Vacuum degassing code
$\Delta C, \Delta Mn, \Delta Si, \Delta Al, \Delta Nb, \Delta B$	Increment values for carbon, manganese, silicon, aluminium, niobium and boron.
C_{min}, C_{max}	Upper and lower values of carbon in the steelmaking aim chemistry.
R1, R2	Governing chemical requirements.
$F_1, F_2, \ldots F_{10}$	Constants to compute upper yield strength.
$T_1, T_2, \ldots T_{12}$	Constants to compute the tensile strength.
A_{ij}	Alternative steelmaking aim chemistry values for various elements.
WSMF	Weighted sum membership function
μ, σ	Mean and standard deviation
PDF	Probability density function.
CDF	Cumulative density function.
z	Standardised normal variable
$\phi(z)$	Standard normal probability density function.
$\Phi(z)$	Standard cumulative density function.
G_j	Grade j.
S_i	Customer order i
$\beta_1, \beta_2, \beta_3, \beta_4$	Weighting coefficients to determine the weighted sum membership function by modified method.
min	Zadeh's minimisation operator.
$f_{(x)}$	Fuzzy membership function.

A_i Coefficients to compute alloying cost component of the relative cost factor.

B_k Constants to compute processing component of the relative cost factor.

E_i Various elements in the steelmaking aim chemistry.

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CHAPTER 1

CHAPTER 1

INTRODUCTION

1.1 THE IMPORTANCE OF CURRENT RESEARCH PROJECT AND ITS OBJECTIVES

1.1.1 Artificial Intelligence in Material Design

The term Material Design is used in this thesis to indicate the design of steelmaking aim chemistry for plates. Steelmaking aim chemistry here refers to the composition of the molten metal produced at the basic oxygen steel making furnace and which has undergone various processes such as ladle injection, vacuum degassing, etc, based on the customer requirements. This is input to the continuous casting machine.

Material design in steel making is a complex task due to the interaction of numerous factors and also because material design problems are ill-structured and difficult to systematise. Material design is also characterised by over-dependence on experts and lack of consistency in the design of steel material. A major portion of the material design knowledge is heuristic in nature. Heuristic knowledge is based on the intuition of experts and the rules of thumb. Many complex factors interact in material design, design specifications vary greatly and more importantly material design knowledge is held in largely intuitive undefined format. This makes the Knowledge Elicitation (KEL) task very difficult and time consuming. As heuristic knowledge component of material

design knowledge requires interview techniques for successful elicitation of this knowledge, the KEL also becomes very expensive due to the experts being highly paid.

The material design system described in this thesis is based on a generation process. It does not involve selecting a solution from a set of previous solutions, but requires the generation of a unique set of solutions for each combination of grade and thickness required by the customer.

To reduce the dependence on experts and to obtain consistent results every time, it is desirable to apply Artificial Intelligence (AI) techniques to the material design process which are characterised by the above restrictions. AI techniques are finding many fruitful applications in industries and in particular in the iron and steel making field. This is because considerable time is saved in the time taken to perform the knowledge intensive complex tasks and more importantly because the uncertainty could be efficiently managed.

Neural network approach is suitable for judgements in which there are no logical connections between input and output, the input and output are well defined, the patterns of input and output are limited to the cases that the system has experience with and exactness is not required. Due to following disadvantages the use of neural network technique was not included in the material design system [63]:

- Difficult to implement logical rules from experts
- Reasoning model is a black box to the experts.
- A large number of data is required.

Knowledge-based systems could be defined as computer systems, comprising both hardware and software that mimic an expert's thought processes to solve complex problems in a given domain [96]. Material design being a knowledge intensive field, the application of knowledge-based system approach would enable automating the design process by utilising the heuristic and expert knowledge of a group of experts.

1.1.2 Significance of the Hybrid Approach Combining Knowledge-Based Techniques and Mathematical Modelling

Material design is also characterised by the utilisation of mathematical modelling which involves enormous computations due to the iterative nature of the design process. Combinations of various alloying elements with appropriate increment values are considered in the design process for steel plates, making any manual material design process too time consuming to be practical. Due to interaction of many complex factors in material design, it is very difficult to systematise the process by the application of the mathematical approach alone. If an attempt is made to design the steel material based on the mathematical approach, it would result in unrealistic designs because the relationships between various design parameters are not always linear. To eliminate these, the research work is focussed on developing a hybrid approach to design steel material.

There is no sound methodology available in the literature reviewed which utilises both the knowledge-based and mathematical modelling approaches to design steel plates. This thesis deals with this complex task of developing a hybrid methodology for designing steel plates utilising knowledge-based and mathematical modelling approaches.

1.1.3 Significance of Ranking Various Alternatives

Ranking of various alternative solutions to a problem considering the main factors involved, is also an important task in industrial applications. This is because a number of practical situations involve more than one solution. This is also the case in the design of steel plates. A number of alternative steel making aim chemistries are possible for any combination of grade and thickness ordered by the customers with varying degrees of desirability.

The approach of generating several alternatives for a customer order instead of a single steelmaking aim chemistry is adopted in this work due to the following two main reasons:

- The process of determining steelmaking aim chemistries is characterised by utilisation of various empirical models which have an error of ± 20 to ± 40 MPa in the prediction of tensile strength and yield strength values. This inaccuracy results in a range of computed values of steelmaking aim chemistries that are feasible for any customer requirements due to the wide tolerance range.

- Having several alternatives is desirable from the optimisation point of view. The optimisation could be achieved by trading off some parameters at the expense of other parameters.

Uncertainty encountered in the process of ranking the steelmaking aim chemistries is probabilistic in nature. Fuzzy logic in conjunction with probability theory could be

successfully applied to model the uncertainty and imprecision inherent in real world problem of ranking these alternatives. This thesis also discusses a methodology to rank steelmaking aim chemistries, considering complexity factor in addition to chemistry, mechanical property and the relative cost.

1.1.4 Objectives of Current Research Project

The main objective of the research project was to develop a methodology to build a prototype system for assisting metallurgists in the design of steel plates and modification of existing steel plate grades based on customer requirements. The methodology developed utilises knowledge-based and mathematical modelling approaches.

As a first step in this direction a new technique to efficiently elicit material design knowledge has been researched. The aim was to reduce the expensive interview time and to simplify knowledge representation resulting in reduced computer storage and also considerably reduced search time.

The hybrid approach combining knowledge-based technique and mathematical modelling was investigated with an aim to develop a methodology which could be successfully applied to the material design process under consideration. An interactive graphical user interface for the prototype system has been investigated to simplify the input information from the customers and to make the system more user friendly.

Finally, the application of fuzzy logic to rank alternative steelmaking aim chemistries generated by the prototype system has been investigated. This was done with an aim to

develop a methodology to realistically rank the alternatives according to the likelihood that the alternatives would meet the customer requirements and would be practically feasible. In this process various constraints or limitations encountered in the production of steel plates were considered.

1.2 SCOPE OF THESIS

This thesis deals with developing a methodology to design steel plates (reversing mill steel product). Strips or the continuous mill products are outside the scope of this research. The approach utilised in the development of the system is hybrid, combining knowledge-based and mathematical modelling. "As rolled" process of rolling steel plates is considered and control rolling as well as normalising processes are excluded from the scope of this research.

The first stage of the thesis discusses newly developed knowledge elicitation technique utilising a codification scheme, non-interview techniques and paper models. Then the thesis discusses the methodology developed to design steel plates utilising the knowledge elicited in the first stage and combining mathematical modelling approaches. The alternative steel making aim chemistries generated by the prototype system are then ranked according to the likelihood of meeting customer requirements without difficulty. The thesis then proceeds to discuss the methodology developed to accomplish the ranking by the application of fuzzy logic. Finally, an interactive graphical user interface has been discussed which makes the input to the system very simple and error free, utilising the codification scheme developed for the knowledge elicitation.

1.3 ORGANISATION OF THE THESIS

The thesis is organised into eight chapters as follows:

Chapter One describes the significance of the current research project and the aimed objectives. It also outlines the scope of the thesis and lists the major contributions made while undertaking this research.

Chapter Two reviews comprehensively the literature available regarding the existing applications of AI and fuzzy logic applied to iron and steel making. The salient features of existing applications and the benefits derived from these are also included in this chapter. The future directions of research in this field are then briefly mentioned. Literature relevant to each of the chapters is also reviewed in the corresponding chapters.

Chapter Three describes the new methodology developed for eliciting knowledge from the expert metallurgists. The elicitation of the expert as well as the heuristic knowledge components is also explained in this chapter. This laid the foundation for the remaining research work described in the succeeding chapters.

Chapter Four deals with the methodology developed to design steel plates combining knowledge-based and mathematical modelling approaches. The basic approach to material design and the iterative process utilised in the design system are also explained in this chapter.

Chapter Five describes the interactive graphical user interface developed to enable quick and error free input of customer requirements to design steel plates utilising the codification scheme developed for the knowledge elicitation process.

Chapter Six describes the ranking of steelmaking aim chemistries generated by the prototype system by the application of fuzzy logic. Development of individual, composite and weighted sum membership functions are described.

Chapter Seven reviews the results generated by the prototype steel plate design system for sample combinations of customer requirements of grade and thickness. The results generated are reviewed vis a vis the actual steelmaking aim chemistries used by the expert metallurgists.

Finally, Chapter Eight concludes the thesis by first summarising the research undertaken, results achieved and limitations of the current research. Important issues to be considered in future research are also highlighted at the end.

List of references follows Chapter Eight.

1.4 OVERVIEW OF PROTOTYPE SYSTEM DEVELOPED

Determination of steelmaking aim chemistries, is a process of considering all the feasible alternative steelmaking aim chemistries and limiting these alternatives by the application of various knowledge-bases. The hybrid approach of knowledge-bases and mathematical modelling has therefore been utilised in the development of the prototype system. Figure 1.1 depicts the main stages in the development of the prototype system.

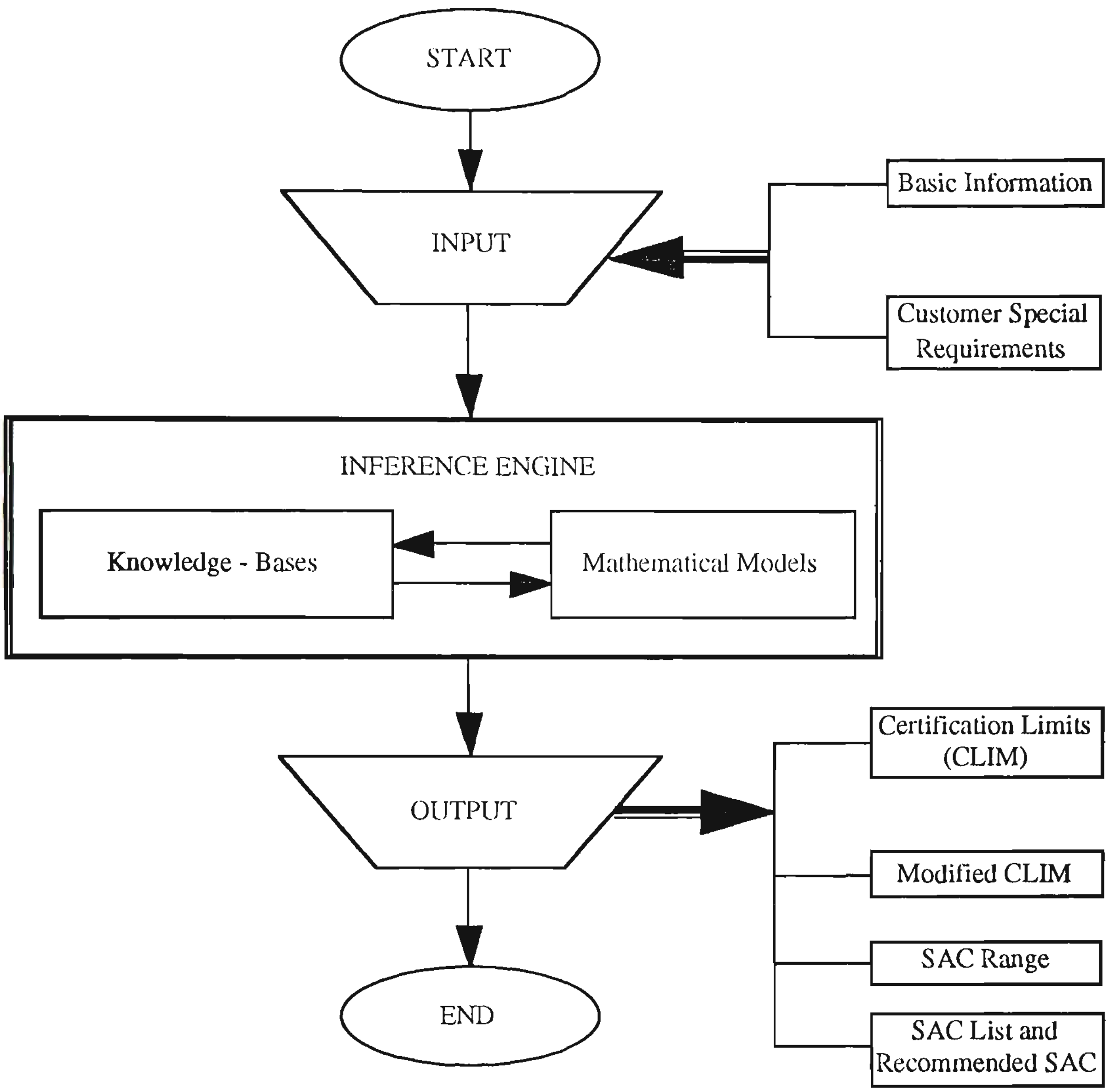


Figure 1.1 Prototype Material Design System

SAC in this figure refers to the steelmaking aim chemistry. SAC is the contents of various elements such as carbon, manganese, silicon, phophorus, sulfur, etc. in the steel plates required by the customer. SACs indicate the elements to be included in the steel and their percentage contents by weight. The input to the system consists of basic information and customer special requirements which is entered into the system through the graphical user interface consisting of two interactive screens shown in Appendix A.

The details of the input process are explained in figure 1.2. The input is through the two sets of interactive screens (Appendix A) developed utilising a codification scheme. Basic information regarding the steel plates ordered by the customer which consists of the steel grade (details from the referenced material standard), thickness, width, length, quantity, tonnage and end use are input through the first input screen.

Knowledge-bases along with mathematical modelling are utilised in the inference engine to generate a list of steelmaking aim chemistries for a combination of grade and thickness required by the customer.

The output consists of the certification limits obtained through matching TABLEAUX rule bases and modified certification limits based on customer special requirements. In addition, the range of steelmaking aim chemistries values or the minimum and maximum values of various elements in steelmaking aim chemistries are also included in the output. All the outputs generated by the prototype system as well as the details of the customer requirements are shown in Appendix D.

The customer special requirements, if any, are input through the second set of screens which are presented to the user after completing the input of the basic information. The customer special requirements are input through the three input fields in the input screen. These fields, via three pull down menus, enable the input of the details of customer special requirements, which are later converted into a code, the Customer Special Requirement Code (CSRC). The three input fields are based on a codification scheme and are utilised to input the type of customer special requirements, the type of material and the values of the customer requirements, respectively. After inputting one set of customer special requirements another input screen is presented to the user to

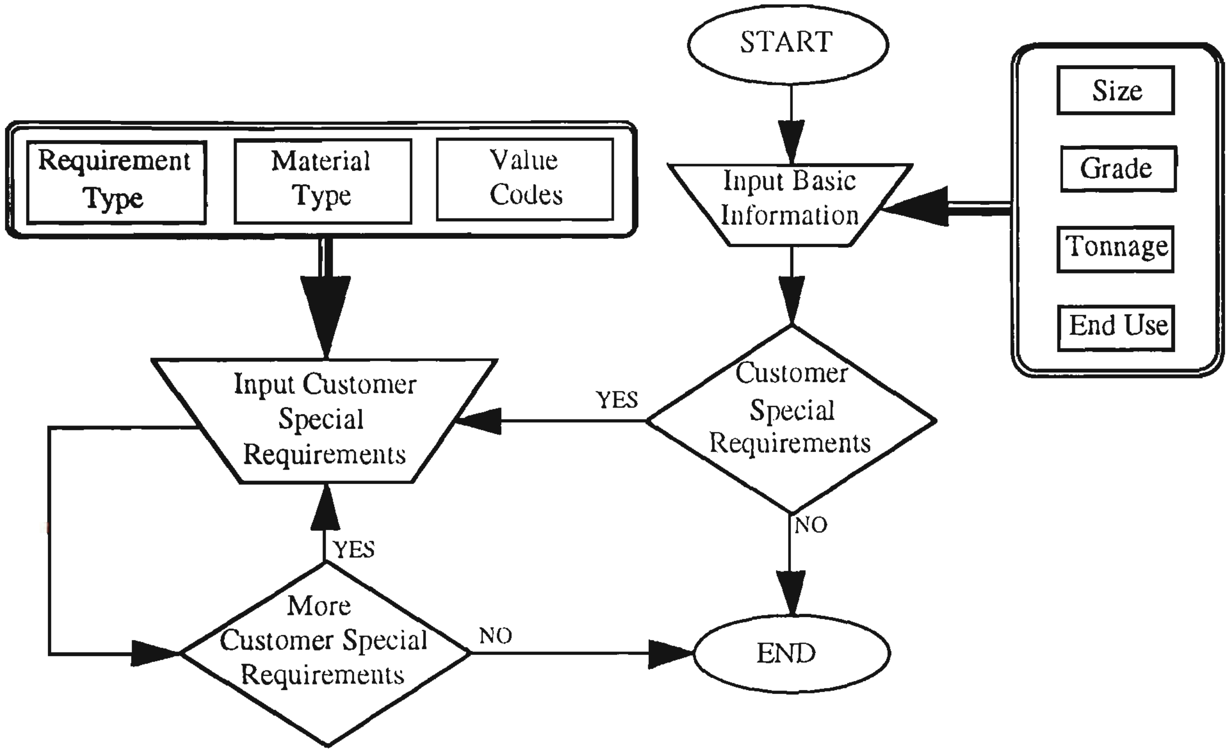


Figure 1.2 Input to the Prototype System

enable input of further customer special requirements until all customer special requirements are detailed (figure 1.2).

1.5 SUMMARY OF CONTRIBUTION

- Material design knowledge has been modelled into two groups to facilitate efficient knowledge elicitation. The two components of the material design knowledge include:

  - Heuristic Knowledge Component and

  - Expert Knowledge Component

- A new technique has been developed to efficiently elicit material design knowledge from expert metallurgists for incorporation into the material design system. This technique utilises:
  - Three character alphanumeric codification scheme for customer special requirements.
  - Non-interview techniques and
  - Paper models.

- Hybrid approach for designing steel plates has been developed which utilises:
  - Knowledge-Based techniques and
  - Mathematical Modelling

- A prototype material design system has been fully implemented in C language based on the above approach. It has been tested using actual technically accurate inputs and has generated correct outputs in sample cases which prove the potential of the proposed methodology.

- An interactive graphical user interface has been developed to input customer requirements based on the codification scheme for the above system. This user interface consists of two sets of input screens to input the basic information and the customer special requirements.

- Methodology to rank the steelmaking aim chemistries generated by the prototype system has been developed by the application of fuzzy logic. This is achieved by computing individual, composite and the weighted sum membership functions for

the four factors viz. chemistry, mechanical property, relative cost and the complexity.

- The complexity component in the above fuzzy ranking has been determined based on a newly developed methodology. An interactive dialogue session has been developed to determine this factor based on the current plant situation.

- A simple and efficient equation has been developed to determine the membership function component of relative cost factor used in the fuzzy ranking. This equation consists of two components:

  - Cost of alloying elements and

  - Cost of processing.

- A system has been fully implemented in C language to accomplish the ranking of the steelmaking aim chemistries generated by the prototype system based on the methodology developed.

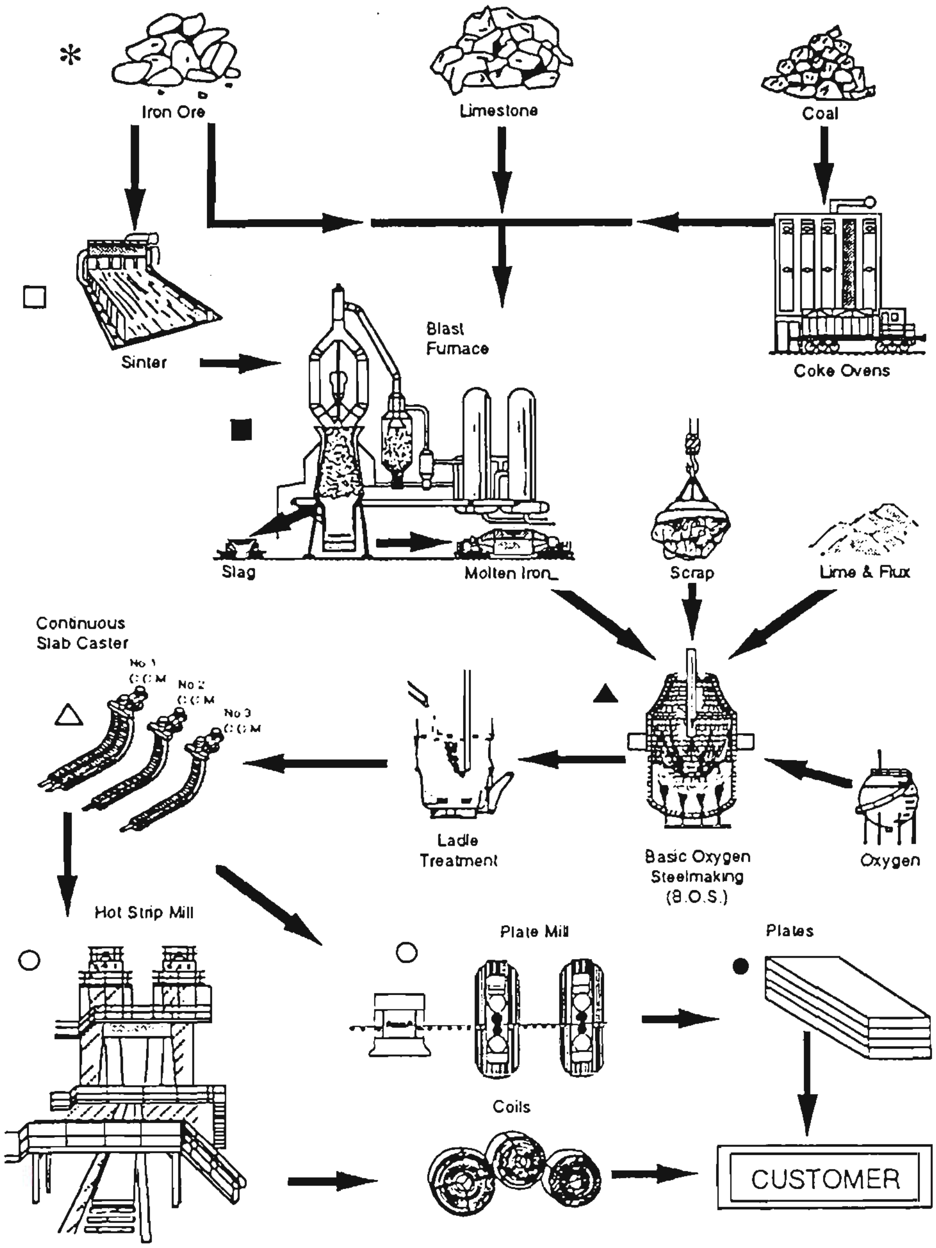
CHAPTER 2

CHAPTER 2

SURVEY OF ARTIFICIAL INTELLIGENCE/FUZZY APPLICATIONS IN IRON AND STEEL MAKING

2.1 INTRODUCTION

The steel industry is facing the need for an increased automation to improve product quality and productivity. The steel makers also face the challenge from non ferrous materials which is expected to intensify further in the future. The operating philosophy of steel makers is also switching from mass production at low unit cost to small volume production at low unit cost, and from higher quality at higher cost to higher quality at reasonable cost. There are several important areas in steel making such as control of blast furnace, scheduling of steel making processes and material design, where the dependence on the experts is very much needed. There are some fields in steel making that have not yet been systematised because of inadequacy of the control theories and operation research methods available today to solve the problems due to difficulties in modelling and dynamically changing operating conditions. These problems are normally solved by the experts who use the vast knowledge which they have amassed over a long period of time, in addition to heuristic and intuitive knowledge which they possess. In order to reduce the dependence on experts and enable reduction in time taken to perform these knowledge intensive complex tasks, and more importantly to efficiently manage the uncertainty it becomes desirable to apply the AI and fuzzy logic techniques to steel making practices.



✱ - Ore Yard Diagnostic [86]

□ - Operator Guidance System [44]
- Burning Control [49]
- Sintering Process Control [33]

○ - Shape Control of Strip & Plate [29]
- Material Design [95]
- Control of Box Annealing Furnaces [102]

● - Machining Performance Prediction [17]

△ - Diagnostic [12], [79]
- Material Design [91-92], [97-98]

■ - Heat monitoring and Control [61], [89]
- Operation and Control [66]
- Setting of Gas Flow rate [49]
- Hopper Discharge Control [31]
- Forecasting Furnace Heat [57]

▲ - LD Converter Processes Control [35]

Figure 2.1 Fuzzy Systems in Iron and Steel Making

2.1.1 Overview of Iron and Steel Making

Before going into the AI/Fuzzy applications in iron and steel making, an overview of the iron and steel making processes is briefly discussed below. The whole processes involved in the production of steel could be classified broadly into three categories:

- Iron Making
- Steel Making and
- Steel Shaping

Iron making is a process of extracting metallic iron from the iron ore in a blast furnace by reduction process. Iron making is a continuous process which uses the raw materials - iron ore, coke and limestone or a baked combination of these known as sinter. The molten iron produced in a blast furnace contains about 4% of carbon and is passed to the steel making process as a liquid at approximately 1450°C, called "hot metal".

Steel making is the process of refining the hot metal from the blast furnace to reduce the carbon content usually to less than 1% by an oxidation process in a steel making furnace. By the addition of alloying materials to the hot metal, the final product is given many of the special chemical and physical properties required. Earlier most steel was produced by the Bessemer and open hearth processes, but now-a-days more modern Basic Oxygen Steel making (BOS) and electric arc furnace processes are employed.

The BOS process uses pure oxygen (99% pure) injected by a lance, for refining the relatively impure hot metal. Further treatment of the steel is done in the ladle which includes bubbling the steel with an inert gas (eg. nitrogen) for thorough mixing of the

alloys and injection of materials to further reduce impurities. For some special steels a vacuum degassing treatment is used to remove dissolved gases, particularly oxygen and hydrogen. The electric arc furnace is primarily a supplier of heat to melt relatively pure scrap or sponge iron, which requires less chemical reaction for refining.

An intermediate process needed before the liquid steel can be shaped into a commercial product is continuous casting which produces slabs. An open-ended, water cooled mould is used to produce the shape required. A ladle of molten steel is positioned above the casting machine and a hole in the bottom of the ladle is opened allowing the liquid steel to pour through a container known as a tundish into the mould, forming the required shape.

The conventional casting process consists of pouring the molten steel from the ladle into moulds to obtain ingots which can then be further reheated and rolled to produce semi-finished shape such as slabs, blooms, and billets. This conventional casting process is now almost entirely being replaced by the continuous casting process which produces steel with more consistent composition, surface finish, and dimension. This process also results in large savings in energy costs.

Steel can be shaped in many ways such as by rolling, casting, forging, welding and pressing. Out of these, rolling is the main technique used. Slabs or billets are heated in a furnace to about 1200 °C, then passed between a pair of rollers held in a large steel frame called a stand. They may be passed back and forth through the same stand several times or proceed once through a number of stands mounted in a row (tandem mills).

2.1.2 Applications of AI Techniques to Iron and Steel Making

The emergence of AI was earlier than that of the computer itself, starting from 1930's, mainly in USA. An expert system is one of the main AI application field and it originated in the Heuristic Programming Project (HPP) in 1960's at Stanford University [101]. In 1970's some practical expert systems were developed which included DENDRAL molecular construction identifying system for organic compounds [11] and MYCIN blood infection disease diagnosis system [76]. The success of these expert systems encouraged further research in this field mainly in laboratories and in 1980's supplemented by the development of expert system building tools and rapid progress in hardware technology it started entering the industries.

In the steel making field the AI approach has been applied to solve diagnostic problems [7], [37], [40-41], [45], [48], [51], [58], [60], [71], [86]; design problems [55], [59], [100]; planning problems [34], [42], [72]; scheduling problems [2], [62], [82-83]; and control problems [1], [3], [15], [32], [36], [65], [70], [86].

Expert System building tools also known as expert system shells have been developed [53], [60], [93] to reduce the time taken to build expert systems for applications in iron and steel making. Even though a large number of expert systems have been developed, only about half of them meet their original targets, as was illustrated by Kawasaki Steel where less than half of the 30 systems developed have been found practically successful. This is due to a lack of research and practical experience which hinders the application development.

Some of the interesting AI applications above include:

- Character recognition system to detect defects in the stencilled characters on the surface of cast slabs based on a three layer neural network model developed by Kawasaki Steel [3].

- Break out prediction system for continuous casting process utilising multi-neural network structure developed by Nippon Steel [40].

- An expert system for material design of large-diameter steel pipe incorporating AI and Operations Research (OR) technology developed by Sumitomo Metals to improve design quality, reduce dependence on expert designers and reduce the time required for design [100].

- A prototype real-time expert system developed by the Steel Resource Centre at North Western University to improve plant-wide quality management in steel companies in US focussing on the hot strip mill [48], [71].

To improve the productivity of the system development, Kawasaki Steel developed its own expert system development guide and expert system development tool [20]. Nippon Steel has developed another expert system shell ESTO which has a distributed cooperative architecture [52]. Similarly Sumitomo Metals has also developed a production type expert system building tool MARKS-II suitable for design, planning, process control and system supervision [84-85].

Fuzzy set theory, a theory of graded concepts is a technique which deals with complex phenomenon which cannot be analysed by classical methods based on probability theory and bivalent logic. Real-world systems are very often uncertain or vague. Fuzzy logic

has been successfully applied to several areas in steel making in which uncertainty or vagueness is inherent and fuzzy expert systems developed which deal with diagnostic problems [12], [86]; blast furnace control problems [66], [89]; design problems [91-92], [95], [97-98]; and control problems [12], [29], [31], [33], [35], [44], [49], [57], [61] and [102]. Figure 2.1 depicts various existing fuzzy systems developed for applications in iron and steel making. The phenomenon of uncertainty can be modelled adequately than is being done so far with the use of fuzzy set theory, in order to capture human thinking and perception through AI. Fuzzy logic uses linguistic variables to describe the fuzziness which makes the communication between the system and human beings easy. Another advantage of using fuzzy logic is that it manages the uncertainties involved in a complex process and can be applied to ambiguity expressions to prevent excessive increase in the number of rules.

The significance of using fuzzy logic to iron and steel making practice can be well demonstrated by taking the example of the control of the blast furnace. Various types of theoretical and statistical models have been developed to control the thermal condition of blast furnace, but none of them is fully successful in controlling the blast furnace in real time operation due to the complex nature of the process which is difficult to describe with equations, the long time lag of the process, and the complex manner in which the three phases i.e. solid, liquid, and gas metallurgically react in the furnace. When the thermal condition is estimated based on the hot metal temperature there is fuzziness inherent which is dependent on the time from the beginning of tapping. The large amounts of sensor data including the hot metal temperature and other data on the furnace condition which are required to judge the thermal condition in the blast furnace are characterised by a certain level of fuzziness. The human judgement based on these information is also ambiguous. This fuzziness or ambiguity can be dealt successfully in

fuzzy logic by applying the membership functions. Similarly the other complex processes in steel making with built-in fuzziness or ambiguity can be effectively handled by applying the fuzzy logic to control the process.

A comprehensive review of the application of AI and expert systems in steel industry has already been undertaken [13]. The purpose of this chapter is to survey several existing applications of AI and in particular fuzzy logic to iron and steel making area and to highlight the benefits derived from the application of AI and fuzzy logic. This is also an attempt to indicate to the researchers the work being done in the area of fuzzy logic applied to iron and steel making and to point to the future direction of research. In this chapter the fuzzy applications in steel making are classified into appropriate categories and the salient feature of each application is reviewed. The trend of developing hybrid systems combining the fuzzy and OR technologies is discussed with the aim of providing a guide to the main fuzzy techniques used. The ongoing research at BHP Steel in the field of AI and fuzzy logic is then briefly discussed. At the end the future trends in the application of fuzzy logic and the areas which need further attention and future research are discussed.

2.2 BACKGROUND OF FUZZY SET THEORY

The theory of fuzzy logic was introduced by Professor Lofti A. Zadeh of the University of Berkeley in 1965 [103]. Conventional computer logic is incapable of manipulating data representing subjective or vague human ideas, such as "an attractive person" or "pretty hot". Computer logic previously envisioned reality only in such simple terms, as on or off, yes or no, and black or white. Fuzzy logic was designed to allow computers to determine valid distinctions among data with shades of gray, working similarly in

essence to the processes which occur in human reasoning. Accordingly, fuzzy technologies are designed to incorporate fuzzy theories into modern control and data processing, to create more user friendly systems and products.

In recent years considerable attention has been given to use fuzzy set theory to quantify the qualitative and approximate evaluations and judgments of human beings. A successful application of using such an idea is the quantitative assessment of total machinability for arbitrary selection of operation parameters including steel materials [16-17].

Nowadays in Japan, fuzzy logic is successfully being applied to industrial systems such as elevators and subways and to an array of consumer electronic products. Convenient fuzzy logic home electrical appliances include washing machines that sense the dirtiness and type of fabric to automatically determine water flow and detergent requirements; and vacuum cleaners capable of detecting not only the presence but the degree of dust on a floor.

Fuzziness in expert systems could be represented mainly by two methods- introduction of a certainty factor into the rules, or through fuzzy theory using membership functions. The central concept of Zadeh's fuzzy-set theory is the membership function which represents numerically the degree to which an element belongs to a set. This function takes on values between 0 and 1. The membership function is assessed subjectively in any instance, small values representing low degree of membership and high values representing high degree of membership.

A brief summary of the basic properties of fuzzy sets such as the membership function, convexity, goals, constraints, decisions, α- Cuts, and cardinality of fuzzy sets described in [5], [14], [103], [106] is given below in order to define the concepts and terms which will be used in this thesis.

Fuzzy Set. If $X = \{x\}$ denotes a collection of objects (points) denoted generically by x, then a fuzzy set A in X is a set of ordered pairs

$$A = \{(x, \mu_A(x))\}, \quad x \in X \tag{2.1}$$

where $\mu_A(x)$ is termed as the grade of membership of x in A and $\mu_A : X \to M$ is a function from X to a space M called the membership space.

Intersection. The intersection of A and B is denoted by $A \cap B$ and defined as the largest fuzzy set contained in both A and B. The membership function of $A \cap B$ is given by

$$\mu_{A \cap B}(x) = Min(\mu_A(x), \mu_B(x)), \quad x \in X \tag{2.2}$$

where $Min(a,b) = a \quad if\ a \leq b \quad and \quad Min(a,b) = b \quad if\ a > b$. In infix form, using the disjunction symbol $\wedge$ in place of "*Min*", equation 2.2 can be written as

$$\mu_{A \cap B} = \mu_A \wedge \mu_B \tag{2.3}$$

Union. The union of A and B denoted as $A \cup B$, is defined as the smallest fuzzy set containing both A and B. The membership function of $A \cup B$ is given by

$$\mu_{A\cup B}(x) = Max(\mu_A(x), \mu_B(x)), \quad x \in X \tag{2.4}$$

where $Max(a,b) = a \quad if\ a \geq b \quad and \quad Max(a,b) = b \quad if\ a < b$. In infix form, using the symbol $\vee$ in place of "*Max*", we can write equation 2.4 as

$$\mu_{A\cup B} = \mu_A \vee \mu_B \tag{2.5}$$

Convexity and Concavity. If A is a fuzzy set in $X = R^n$ then A is convex if and only if for every pair of points x, y in X, the membership function of A satisfies the inequality

$$\mu_A(\lambda x + (1-\lambda)y \geq Min(\mu_A(x), \mu_A(y)) \tag{2.6}$$

for $0 \leq \lambda \leq 1$, where R is a set of real numbers. Conversely, A is concave if its complement A' is convex.

Decision. Intuitively, a decision is basically a choice or a set of choices drawn from the available alternatives. If a fuzzy goal G and a fuzzy constraint C are given in a space of alternatives X, then, G and C combine to form a decision, D, which is a fuzzy set resulting from the intersection of G and C. Symbolically

$$D = G \cap C \tag{2.7}$$

and correspondingly
$$\mu_D = \mu_G \wedge \mu_C \tag{2.8}$$

More generally, if n goals $G_1, G_2,...G_n$ and m constraints $C_1, C_2,...C_m$ are given, then the resultant decision is the intersection of the goals $G_1, G_2,...G_n$ and the given constraints $C_1, C_2,...C_m$. That is

$$D = G_1 \cap G_2 \cap .... \cap G_n \cap C_1 \cap C_2 \cap .... \cap C_m \qquad (2.9)$$

and correspondingly $$\mu_D = \mu_{G_1} \wedge \mu_{G_2} \wedge .... \wedge \mu_{G_n} \wedge \mu_{C_1} \wedge \mu_{C_2} \wedge .... \wedge \mu_{C_m} \qquad (2.10)$$

The relation between goal, constraint, and decision is depicted in figure 2.2. In defining a fuzzy decision D as the intersection or, more generally, as the confluence of the goals and constraints, it is assumed that all of the goals and constraints that enter into D are, of equal importance. However, if some of the goals and perhaps some of the constraints are of greater importance than other, then D might be expressed as a convex combination of the goals and constraints, with the weighting coefficients reflecting the relative importance of the constituent terms. More explicitly, $\mu_D(x)$ may be expressed as

$$\mu_D(x) = \sum_{i=1}^{n} \alpha_i(x) \mu_{G_i}(x) + \sum_{j=1}^{m} \beta_j(x) \mu_{C_j}(x) \qquad (2.11)$$

where α_i and β_j are membership functions such that

$$\sum_{i=1}^{n} \alpha_i(x) + \sum_{j=1}^{m} \beta_j(x) \equiv 1 \qquad (2.12)$$

Subject to this constraint, then, the values of $\alpha_i(x)$ and $\beta_j(x)$ can be chosen in such a way as to reflect the relative importance of

$G_1, G_2,..., G_n$ and $C_1, C_2,..., C_m$.

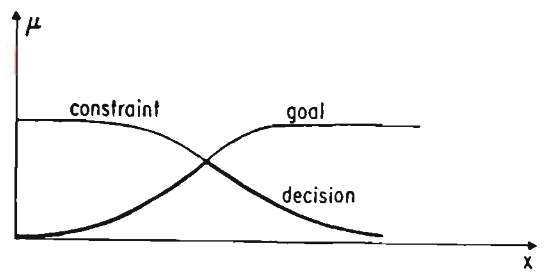


Figure 2.2 Relation between Goal, Constraint, and Decision [5]

α-Cuts. To exhibit an element $x \in X$ that typically belongs to a fuzzy set *A, its* membership value may be demanded to be greater than some threshold $\alpha \in [0,1]$. The ordinary set of such elements is the α-cut A_α of *A* given by

$$A_\alpha = \{x \in X, \mu_A(x) \geq a\} \qquad (2.13)$$

The strong α-cut may be defined as $A_{\bar{\alpha}} = \{x \in X, \mu_A(x) > \alpha\}$ (2.14)

The membership function of a set A can be expressed in term of the characteristic function of it's α-cuts by

$$\mu_A(x) = \underset{\alpha \in [0,1]}{Sup} \min(\alpha, \mu_{A_\alpha}(x)) \qquad (2.15)$$

where

$$\mu_{A_\alpha}(x) = \begin{cases} 1 & iff \quad x \in A_\alpha \\ 0 & otherwise \end{cases} \qquad (2.16)$$

and "Sup" denotes the supremum.

Cardinality of a Fuzzy Set. If X is a finite set, the cardinality (scalar) $|A|$ of a fuzzy set A on X is defined as

$$|A| = \sum_{x \in X} \mu_A(x) \tag{2.17}$$

The relative cardinality can be defined as $\|A\| = {|A|}/{|X|}$ (2.18)

and can be interpreted as the proportion of elements of X that are in A.

The cardinality of a fuzzy set A which should be a fuzzy number and which has finite support is given by

$$|A|_f = {\Sigma \alpha}/{|A_\alpha|} = \{(n, \alpha),\ n \in N\} \tag{2.19}$$

and

$$\alpha = Sup\{\lambda, |A_\lambda| = n\}, \tag{2.20}$$

where A_α denotes the α-cut of A and N is a set of natural integers.

Equations 2.1 to 2.20 are all related to the fuzzy ranking process described in chapter 5. As an extension to the research described in chapter 5, further research could be undertaken to utilise the WSMFs in trading off some parameters at the expense of others. This could be undertaken with twin aims of minimising the number of grades used to produce the customer order and to maximise the likelihood that the customer requirements will be satisfied without difficulty. These equations provide the theoretical basis to accomplish this task.

Table 2.1 Classification of Fuzzy Systems in Steel Making

Developed By	Application	Type	References
BHP Steel	Diagnostic of Cobbles in Strip Mill	Diagnostic	[51]
Kawasaki Steel	Belt Conveyor Control	Diagnostic	[86]
Rautarauukki Oy	Continuous Steel Casting Diagnostic	Diagnostic	[12]
Nippon Steel	LD Converter Process Control	Control*	[35]
Nippon Steel	Control of Box Annealing Furnaces	Control	[102]
Nippon Steel	Shape Control for Cold Strip Mill	Control	[29]
Nippon Kokan	Sintering Process Control	Control	[33]
Nippon Kokan	Blast Furnace Control	Control*	[61], [89]
Kawasaki Steel	Control of Hopper Discharge Rate	Control	[31]
Kawasaki Steel	Burning Control of Sintering Machine	Control	[49]
Kawasaki Steel	Hot Stove Combustion Control	Control	[49]
Kawasaki Steel	Ore Yard Operation Control	Control	[86]
BHP Steel	Sinter Plant Operator Guidance System	Control	[44]
Kobe Steel	Forecasting Furnace Heat	Control	[57]
Sumitomo Metals	Blast Furnace Control	Control*	[66]
Bethlehem Steel	Optimal Metallurgical Grade Design	Design	[91-92], [97-98]
Nippon Steel	Material Design	Design*	[95]

* Expert System Building Tool or Expert System Shells used.

In recent years considerable attention has been given to fuzzy set theory, which makes it possible to quantify the qualitative and approximate evaluations and judgments of human beings. Among its other uses, fuzzy control is a method of controlling manufacturing equipment by expressing the empirical knowledge of expert operators regarding control practices in the form of production rules. Suitable objects of fuzzy control include non-linear systems; systems for which it is difficult to make precise mathematical models and system in which dynamic characteristics vary.

2.3 APPLICATIONS OF FUZZY LOGIC IN IRON STEEL MAKING

The applications of fuzzy logic in iron and steel making could be classified into the following three main categories- Diagnostic, Control and Design. The design category includes the planning and scheduling applications also. Diagnosis problems can be further divided into three main categories: equipment diagnosis, operational diagnosis and product quality diagnosis. Table 2.1 depicts the above categories of fuzzy systems developed for iron and steel making applications.

2.3.1 Diagnostic Applications

Diagnostic problems are easier to handle than planning problems from the view point of the amount of computation involved and hence a large proportion of AI/Fuzzy applications developed are of diagnostic type.

Fuzzy expert system for continuous steel casting diagnosis based on an artificial neural network called productive neural network is developed and implemented at Rautaruukki Oy, Raahe works in Finland [12]. Productive neural networks are a kind of neural

Table 2.2 Knowledge-Base Representation*

Input Casting Variables							Diagnostic Results	
liquid steel superheat ladle treatment	heat content of ladle	mass of skull in ladle	holding time of ladle before casting	ladle stirring time	ladle position in the casting sequence	ladle casting time	problems at the beginning of casting	problems at the end of casting
H	FH	L	FL	FL	FL	FL	No	No
H	FH	FL	L	L	FL	L	No	No
H	FH	FL	L	FL	L	FL	No	No
H	FH	FL	L	FL	L	L	No	No
H	FH	FL	L	FL	FL	L	No	No
H	FH	FL	L	FL	FL	FL	No	No
H	FH	FL	FL	FL	FL	L	No	No
FL	L	L	L	L	L	L	Yes	No
FL	L	L	FL	L	FL	L	Yes	No
FH	FH	L	FL	FL	FL	L	Yes	No
H	FH	L	L	L	L	L	Yes	No
H	FH	FL	FL	FL	L	L	Yes	No
L	L	L	L	FL	FL	FL	No	Yes
FL	L	L	L	L	L	FL	No	Yes
FL	L	L	FL	L	FL	FL	No	Yes

* Reorganised based on [12]

L- Low; FL- Fairly Low; FH- Fairly High; and H- High.

networks developed specifically for fuzzy logic based reasoning. Heuristic knowledge is acquired from the operational experience of engineers and operators partly in the form of a decision tree. This heuristic knowledge has qualitative data partly in the form of a decision tree for the effect of some central variables on the outcome of the casting process. This was represented in a tabular form and a part of it is shown in table 2.2.

It is claimed that this approach may save a lot of time in developing the expert system. Further reasoning is almost instantaneous and no expensive expert system development tools are required. The work demonstrated that productive networks can be used for convenient storage and retrieval of the knowledge for use in a fuzzy expert system. Decision making in continuous steel casting to decide whether to accept or reject the liquid content of a steel ladle (heat) was tackled by using productive neural networks.

A system was developed at Mizushima works of Kawasaki Steel for the operation of the complicated connecting parts of the belt conveyor system [86]. The system for conveyor control is forward looking production system using IF-THEN rules, and it uses fuzzy certainty factor to express human priority judgments and success probability rates. The system has over 100 rules including system diagnostic rules and operation guidance rules. It is reported that the belt conveyor control system has resulted in automatic operation control of complicated belt conveyor connections.

2.3.2 Control Applications

Control problems are becoming important applications of fuzzy logic in steel making. These problems find applications mainly in the blast furnace and sintering machine

which are characterised by complex reactions and thus difficult to be expressed by numerical models.

Nagoya works of Nippon Steel have developed a shape control system for cold strip mill [29]. The actual shape of strip being rolled is detected by a shape meter and is feed back controlled by work roll bending, screw down levelling and coolant zone control. The shape control system is characterised by the application of fuzzy set theory in improving control accuracy. The manipulated variables are determined by control on the basis of fuzzy set theory. The shape deviation for the example of work roll bending is evaluated in detail by a membership function on a seven-point scale from Positive Big (PB) to Negative Big (NB) as illustrated in figure 2.3. The centre of gravity of the entire shaded area is calculated to determine the required change in work roll bending force (ΔRBF).

NB: Negative Big PS: Positive Small

NM: Negative Medium PM: Positive Medium

NS: Negative Small PB: Positive Big

'0': Zero

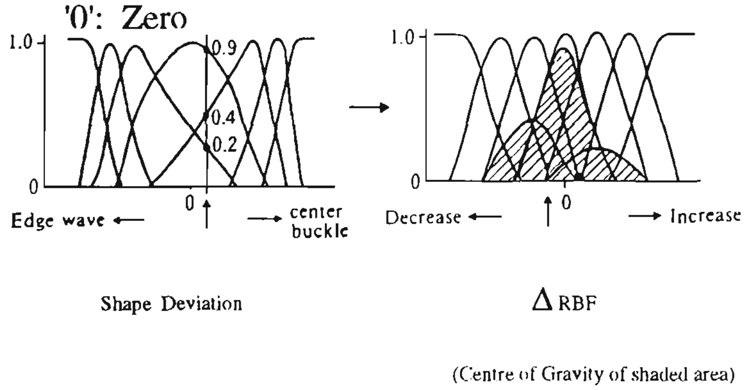


Figure 2.3 Shape Deviation Evaluation by Membership Function [29]

The necessary change in work roll bending force is determined accordingly. The change to be made in screw down levelling is similarly determined. The logic of coolant flow change determination is according to the control rules that consider the rate of change in the shape deviation as well as the shape deviation itself. It is claimed that this system has greatly contributed to the improvement of productivity and product quality.

The expert system developed by Nippon Kokan Co. Ltd. (NKK) for blast furnace control consists of "an abnormal condition forecasting system" which forecasts abnormal in-furnace conditions such as burden slip or channelling and "a furnace heat monitoring and control system" which controls the furnace heat represented by molten iron temperature [61], [89]. The in-furnace condition surveillance utilises sensor data and heuristic rules of the knowledge-base. The furnace heat monitoring and control expert system reasons the current furnace heat level and to which direction the furnace heat is proceeding, and applies the control rules as a result. The expert system describes the expert knowledge needed for extrapolations using three representation methods: production rules, frame-type knowledge, and LISP functions. A greater proportion of the heuristic knowledge, which provides the frame-work of the system is represented by production rules. This system consists of about 400 production rules and 130 frames. The 400 production rules are divided into several Knowledge Sources (KSs) according to attributes. To deal with the fuzziness present in the large amount of sensor data required to judge the thermal condition, certainty factors are given to actual data and 3-dimensional fuzzy membership functions are applied. The self-learning of membership function is illustrated in figure 2.4. If the hot metal temperature to be controlled deviates considerably from the target value, the membership function is re-established. The aim of introducing fuzzy theory in the process to determine a fuzziness is to prevent expansion of system rules and simplify knowledge representation. The system is in

practical use and is reported to be operating favourably, after having undergone modifications as necessary and setting several other new rules.

Control of hopper discharge rates of blast furnace at Kawasaki Steel is done through a system utilising fuzzy logic [31]. Fuzzy control is applied to unloading from the ore bin and the control rule used by the skilled operator is applied to adjust the gate opening by fuzzy inference and feed-back. The fuzzy variables involved in this are the gate opening,

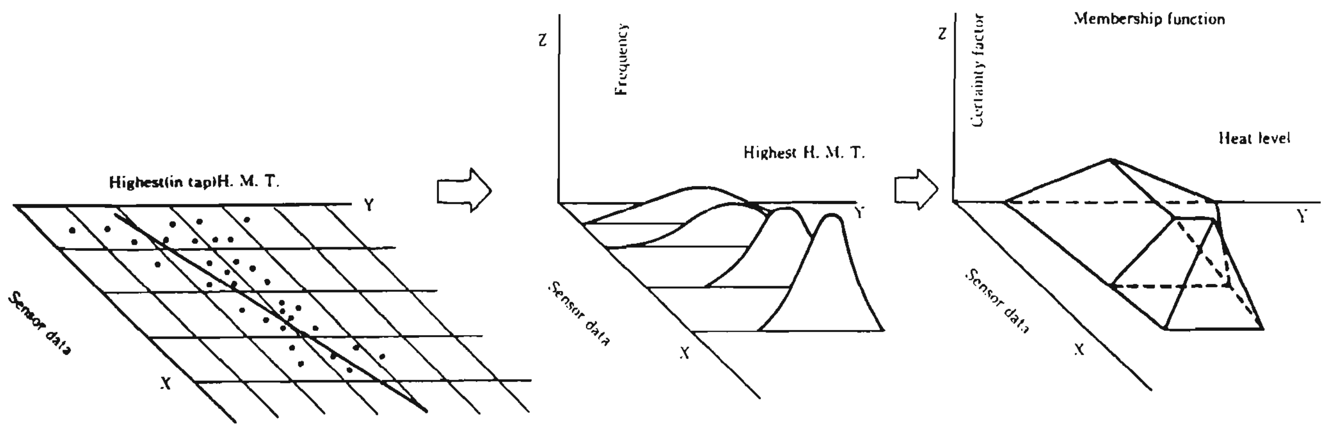


Figure 2.4 Self Learning of Membership Function [89]

the actual discharge rate and the predicted rate deviation. This grain control method uses fuzzy logic to achieve real-time and high speed operation by PLC and the logic type IF-THEN control algorithms are used in parallel. It is claimed that this system has resulted in faster response in unloading control from the ore bin, than was possible with the manual method and the segregation of material brands during raw material discharging is eliminated.

In the sintering plant at Mizushima works of Kawasaki Steel a fuzzy control system for uniform burning control was developed [49]. Fuzzy control was applied to the control of charged density (cut volume), where it is used to operate five-split sub-gates based on the information obtained by waste gas thermometers installed at four points in the width direction along five lines in the longitudinal direction. Inference is conducted based on 28 fuzzy production rules with temperature deviation as the IF part and cut volume at each point in the width direction as the THEN part. It is reported that burning rate uniformity in the pallet width direction was improved considerably .

Fuzzy control was implemented at blast furnace of Kawasaki Steel to the setting and calculation of the gas flow rate and calorie levels during combustion, based on information on the residual stove heat value and brick temperature distribution [49]. Fuzzy inference is conducted based on 36 rules. It is claimed that automatic setting of the gas volume has resulted in an increase of about 3% in thermal efficiency.

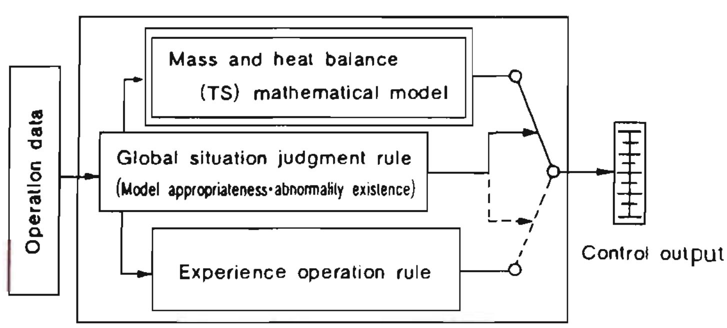


Figure 2.5 Hybrid Control System [66]

Sumitomo Metals had developed a hybrid expert system similar to fuzzy control system for blast furnace operation incorporating the numerical model and the knowledge-based

approach utilising experience rules [66], as depicted in figure 2.5. This system combined the advantage of model controllability at the stationary state with the advantage of experience rules at the non-stationary state. It is aimed at controlling the blast furnace stably for a long time by use of a general situation judgment rule and by checking model appropriateness. Data processed in an existing process computer and numerical model computation results are sent to the AI microcomputer every 2-10 minutes through a network, where the data is analysed and decisions on various kinds of data received is made. The application possibility of the blast furnace condition model is judged and operation action taken mainly from experience rules whenever necessary. Diagnosis results are displayed on a CRT every 10 minutes, data transmission is made to the process computer and data is output through an automatic control system in the process computer. As in most of the expert systems at Sumitomo Metals, the expert system building tool MARKS-II.RT was used in developing this hybrid expert system. It is claimed that the scattering in the hot metal temperature and the silicon percentage in hot metal are remarkably lowered in comparison to the conventional manual control.

Remote automatic control system for sizing plant to control the crusher clearance and apron feeder was developed using fuzzy control with the aim of labour saving and energy saving at Kawasaki Steel, ore yard operation [86]. Development of fuzzy control system involved the development of a crushing-state estimate model using the electric current value and electric power value, preparation of a control logic based on operation know-how, testing of the control logic and parameter tuning. The control logic incorporates fuzzy theory, and is composed of an energy saving logic and quality control logic. It is claimed that this system consistently maintains the size distribution of crushed products within specified range.

Fuzzy logic has been successfully applied to the control of iron ore sintering process at Nippon Kokan Company (NKK) in Japan [33]. It is reported that the deviation of return fine hopper level decreased from 12 to 4% and the amount of return fine ore decreased by about 2 Kg per ton, resulting in considerable reduction in product cost.

Nippon Steel has developed an expert system (LD-ES) to control the LD converter processes [35]. The main objectives of the system included improved blowing accuracy, labour savings and increased flexibility. The system has two modules- static control and dynamic control. Static control utilises rule based reasoning based on the empirical knowledge of the operators to correct errors in the control variables. Dynamic control is realised through fuzzy reasoning where membership functions are used to define the reliability of condition and conclusion parts. An example of membership function used for the estimation of phosphorous concentration is shown in figure 2.6. As a large number of process information X_i are involved for estimating the phosphorous concentration, the final phosphorous concentration is predicted by calculating the weighted mean of all the rules. Fuzzy reasoning is also used to estimate slag formation. The fuzzy reasoning resulted in a reduction of a number of rules and hence the reasoning speed. It is reported that the LD-ES performed better than a skilled operator in controlling the LD converter processes.

Another fuzzy expert system has been developed to estimate the furnace heat from hot metal temperature [57]. The system has been implemented at No. 3 blast furnace at Kobe Steel, Japan and it is reported that it has resulted in successful forecasting from 60% to 86%.

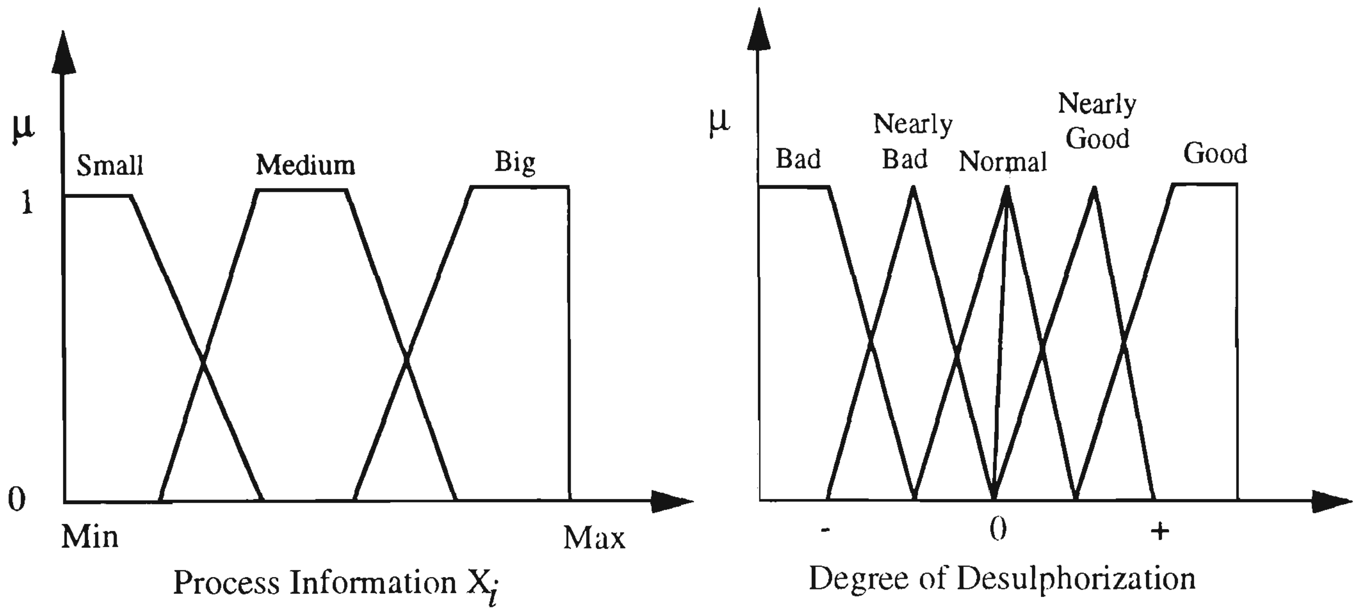
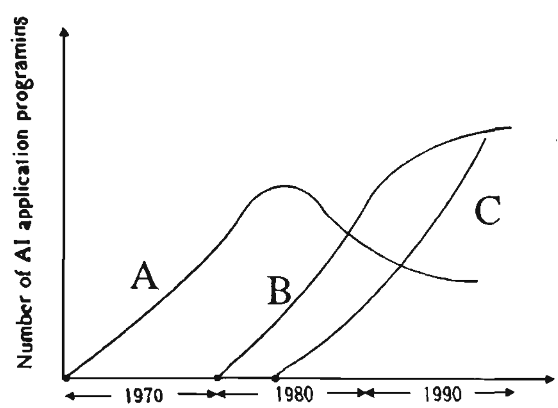


Figure. 2.6 Membership Functions used for Phosphorus Concentration Estimation [35]

The control of box annealing furnaces has been achieved at Nippon Steel by applying fuzzy logic [102]. In box annealing the coil weight and size differ from charge to charge and so the heat transfer characteristics also vary. Due to this the traditional PID controllers are not very effective. A fuzzy expert system having some 22 rules combined with simulation techniques was used for the control of furnaces.

2.3.3 Design Applications

The design problems are usually ill structured, difficult to systematise and a large number of rules are involved and hence the design problems have been given priority in fuzzy applications to steel making. The current trend in the growth of AI/Fuzzy applications as shown in figure 2.7, is in design and planning systems. In the field of



A- Diagnosis Type; B- Planning Type; C- Finance and Economy Type

Figure 2.7 Trend in the AI/Fuzzy Applications [99]

material design, many complex factors interact and the design standards also frequently change due to introduction of new materials.

A fuzzy set based system has been developed at Bethlehem Steel Corporation, USA, for optimally assigning metallurgical grades through a combinatorial optimisation formulation and a heuristic solution procedure [91-92], [99-98]. In this system a list of all applicable grades is prepared by utilising the metallurgical expertise and statistically derived predictive equations along with the characteristics and past performance of every grade and various standards. This list is then ranked according to their membership functions based on the mechanical properties, chemistry requirements, and desirability of producing the grades. The weighted sum membership functions are computed by summing up the composite membership function components which are weighted, based on the equation

$$f_{A(i)}(G_j) = \begin{cases} \alpha_1 f_{K(i)}(G_j) + \alpha_2 f_{L(i)}(G_j) + \alpha_3 f_p(G_j) \\ \qquad if \ \min\{f_{K(i)}(G_j), f_{L(i)}(G_j)\} \neq 0 \\ 0 \qquad if \ \min\{f_{K(i)}(G_j), f_{L(i)}(G_j)\} = 0 \end{cases} \tag{2.21}$$

where L refers to the chemistry and P is a fuzzy sub set of G indicating the plant's desirability of producing grade Gj. $\alpha_1 + \alpha_2 + \alpha_3 = 1$ and $\alpha_1 > \alpha_2 > \alpha_3$. αs are determined based on metallurgical considerations.

Optimisation to reduce the number of grades melted and to maximise the likelihood of meeting all customer specifications without difficulty is then done using several alpha-cut offs together with the defined weighted sum membership functions.

To design steel grades which are not standard, a design type expert system was developed and implemented at Nippon Steel's head office and Sakai works [95]. The core of the system is the reasoning function that performs the manufacturability study. The system gives a concrete form to the expertise and thinking capability of the expert engineers by making the best use of various reasoning techniques like case-based reasoning, neural network reasoning, fuzzy reasoning and hypothetical reasoning. The system was built using the expert system building tool ART™.

Case-based reasoning employed in this expert system was extremely effective in reduction in knowledge acquisition load and simplification of system as well as in increasing the efficiency of problem solving. However, due to limitations of this approach as discussed in chapter 3, it was not utilised in the present work. The neural network utilised cases as learning data and was effective in reducing the knowledge acquisition load and simplification of the system. The fuzzy reasoning technique applied

to the expert system proved effective in raising the reasoning accuracy and simplifying the system configuration without difficulty. Fuzzy reasoning was applied to judge whether the specified toughness can be guaranteed as explained in figure 2.8. Fuzzy reasoning is applied to the differences in the fracture appearance transition temperature and average absorbed energy between the past similar product and the enquired product. The judgement rules used include:

- If the temperature difference is large (to degree 1.0) and the average absorbed energy difference is zero (to degree 0.8), the specified toughness property can be guaranteed (to degree 0.8), R-1 in figure 2.8.

- If the temperature difference is large (to degree 1.0) and the average absorbed energy difference is large (to degree 0.2), the specified toughness property cannot be guaranteed (to degree 0.2), R-2 in figure 2.8.

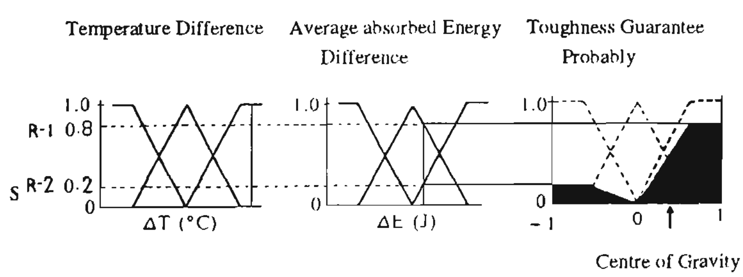


Figure 2.8 Fuzzy Reasoning for Toughness Prediction [95]

The chemical composition design was systematised through the application of hypothetical reasoning based on the Assumption based Truth Maintenance System (ATMS). Hypothetical reasoning assumes that knowledge or information is true, and then verifies the validity of the assumed knowledge or information. When there are two

or more solutions, ATMS-based hypothetical reasoning has the function of extracting all solutions. When the evaluation function is added to the extraction function, optimum design results can be selected. This expert system was put into operation in May 1990 and it is claimed that it has shortened the product manufacturability study task time to one-sixth. The higher-order reasoning techniques adopted in the expert system result in reduction in the knowledge acquisition load, system simplification, and enhancement of the problem solving efficiency.

2.4 RESEARCH IN AI AND FUZZY LOGIC AT BHP STEEL

Since 1984 BHP Steel has been involved in researching the applications of AI in iron and steel making. It has successfully developed and implemented a prototype Operator Guidance System (OGS) for an iron and ore sinter plant in 1986 [44]. It has also developed a diagnostic expert system for the hot strip mill downcoiler [45], which uses knowledge-base approach to analyse both operational heuristics and process data in a structured manner. This system was implemented at Western Port hot strip mill of the coated products division.

BHP Central Research Laboratory has developed a System for Heuristic Real-time Process Assistance (SHERPA) which is a prototyping tool integrating modules for knowledge-base development, signal processing, operator displays, on-line numerical models and database storage. TABLEAUX [9], [10], [26], [44], [77] is another tool which has been developed. It is a decision table based knowledge acquisition tool. TABLEAUX can be used along with SHERPA for developing real-time expert system applications. The limitations of TABLEAUX in the areas of knowledge structuring and use of decision tables as a representational format have been addressed in CAKE (for

Computer Assisted Knowledge Engineering), which is developed as a successor to TABLEAUX. CAKE helps in end-user maintenance of knowledge and serves as a central knowledge repository system supporting multiple applications. It utilises ANSI standard SQL databases as its underlying storage and representational method and provides an extensive set of tools to maintain knowledge dependencies. Some of the salient features incorporated in CAKE from the user point of view include:

- Dependency Chart Editor
- Attribute Editor
- TABLEAUX Decision Table Editor
- Formula Editor
- View Editor and
- Evaluators for Formulae and Decision Tables

CAKE was not available during the initial stages of this research and hence its utilisation in the development of the prototype material design system could not be investigated. However, during the final stages of the research it was available for trial. It was attempted to convert a part of the material design system into CAKE environment. Due to some short comings in the present version of CAKE, the attempt was not very successful. The ability of CAKE in handling a large number of input and decision parameters in applications such as material design was found to be unsatisfactory. The processing time was quite high and the computer screen looked messy in displaying a large number of input and decision parameters as well as their dependencies. However, these problems are being addressed in the current version of CAKE.

The AI applications utilising SHERPA and TABLEAUX facilities currently being developed include:

- Sinter plant OGSs at the Slab and Plate Products Division (SPPD) at Port Kembla and the Rod and Bar Products Division (RBPD) at Newcastle.

- Caster quality assurance applications for RBPD and SPPD.

- Blast furnace OGSs for RBPD, SPPD and the Long Product Division (LPD) at Whyalla

- Prototyping of a basic oxygen steel making OGS for LPD.

- Interactive Scheduling Assistant for SPPD and RBPD.

2.4.1 Fuzzy Logic based SPPD Sinter Plant OGS

A prototype sinter plant OGS which utilises fuzzy logic to determine the strength of the recommended parameter has been developed at BHP Steel [44]. Sample data set were taken from the SPPD sinter plant data acquisition computer and transferred to the SHERPA work station. The pre-processing and operator display modules were used to process and display the data to the expert's satisfaction. Previously developed knowledge-base was entered into TABLEAUX for analysis and modification in conjunction with the expert. The TABLEAUX rule set was then transferred into a NEXPERT™ knowledge-base for off-line testing. A high level interpreted language

SHERPATALK program was prepared to read from the data set, then process and display the data and recommendations to the expert.

Fuzzy logic theory is used to determine the strength of each parameter, which is then displayed graphically on a gauge to the left of the parameter's time series trace. The strength value is determined by locating the data point on a linear membership function. The upper and lower limits for the membership functions are determined by the experts. The determination of fuzzy strength for a single parameter is depicted in figure 2.9.

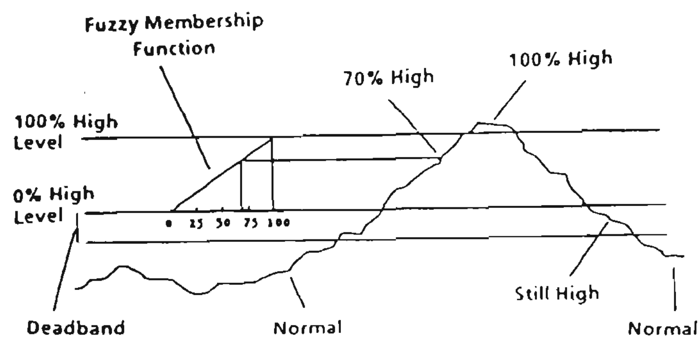


Figure 2.9 Fuzzy Strength Determination [44]

The strength of a recommendation is determined by selecting the minimum strength parameter from the condition parameter of a rule match. If more than one rule contributes towards the truth of a particular hypothesis, the highest strength rule arbitrarily has its strength assigned to that hypothesis. The recommendations and its relative strength are then displayed graphically on the action gauges. Fine tuning can be achieved through the adjustment of the shape of membership functions or the methods by which they are combined.

2.4.2 Interactive Scheduling Assistant

A scheduling system known as an Interactive Scheduling Assistant (ISI), to sequence production flow has been developed and implemented at BHP - SPPD and RBPD [23-26]. This system utilises a strategy that combines the approaches of automation and optimisation through operations research and artificial intelligence. This system also utilises human supervised sequencing through computer tools. Phased development approach has been utilised to minimise the risk of failure. User-maintainable knowledge repositories and user-centred interactive design strategies proved to result in increased acceptance and sense of ownership of the system by the user and hence of smooth implementation with a gradual increase in both cost and risk.

User-maintainable knowledge-bases were developed utilising the knowledge acquisition and browsing tool CAKE. Production personnel at SPPD are currently maintaining and extending knowledge-bases that were initially built by trained knowledge engineers. The knowledge-base currently consists of over 40 decision tables and 15 computational expressions, approximately half of which have been added by the production personnel.

2.4.3 Expert Guidance System for Cold Rolling of Stainless Steel

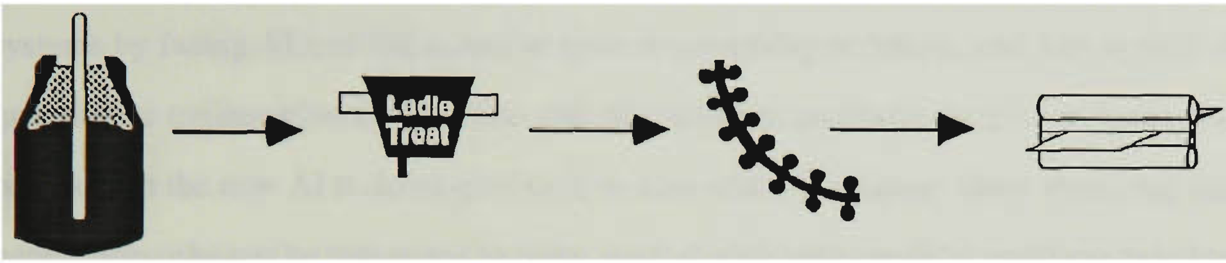
This prototype system is called SENDX and utilises shallow rule based knowledge of the expert mill operators along with deeper physical models from both the rolling theory and metallurgical domains [79]. The system aims in generating suitable schedules which are tested and adjusted against the well established practices of the operators. The system consists of three modules to analyse the proposed schedules: WORK HARD to predict the work hardening behaviour of the steel grade, STRESS to predict the specific

tensions and rolling pressures needed to overcome the material yield stress and ROLL BITE to deduce final roll force and tension forces.

The system utilises VP-EXPERT system shell. The benefits include formalising the expert's rolling knowledge aiding in training of new rolling personnel, demonstrating a methodology in compiling new additional shallow knowledge for the mill operators and highlighting the knowledge gaps in both the fundamental heuristic knowledge-bases and deeper knowledge of the companion models.

2.4.4 Hybrid Material Design System

This thesis discusses the development of a material design system at BHP steel which is described in references [18], [73-75]. Figure 2.10 shows various major processes involved in the steel making process along with the number of products involved at each stage. At each stage the number of products increases and finally at the plate mill there are in excess of 1300 products coming out. The main objective of this research is to determine the steelmaking aim chemistry utilising iterative and knowledge-based approaches. A list of alternative steelmaking aim chemistries is obtained and then fuzzy logic is applied to rank these aim chemistries based on the likelihood of the grades meeting the mechanical properties, chemical composition, cost and complexity of producing the grades, mainly based on the capacity of bottleneck production unit. This is done by defining fuzzy membership functions describing the ability of the grades in meeting the mechanical properties, chemical composition, cost and the complexity. The membership functions are essentially the probability density functions assuming that all the properties under consideration are normally distributed. The system utilises various knowledge bases along with various databases and statistically derived empirical



BOS (207) | Ladle (265) | Caster (940) | Plate Mill (1313)

Figure 2.10 Major Steel Making Processes and Number of Products

relations to determine the appropriate metallurgical grades satisfying the customer requirements.

2.5 CONCLUSION AND FUTURE PROSPECTS

Iron and steel making is an area which demands the application of AI/Fuzzy techniques to systematise the processes, reduce the dependence on experts, to reduce the time taken to perform the knowledge intensive complex tasks and more importantly to efficiently manage the uncertainty or fuzziness and ambiguity. In spite of the diversity and complexity of iron and steel making processes, an attempt has been made to identify a common core of techniques from AI and Fuzzy systems that may be applied to solve the problems in the bottleneck areas in iron and steel making. A review of various AI/Fuzzy techniques used in iron and steel making is presented stressing the higher order reasoning techniques and the salient features of the successful systems. The later half of 1980's has been a period in which more and more problems in the steel making field were tackled successfully through the use of AI applications, especially the hybrid type

of fuzzy systems using AI and OR technologies. This recent trend of developing hybrid systems by fusing AI and OR seems to be very promising in future, with OR applied to quantitative optimisation computation and AI applied to qualitative inference. It can also be said that the new AI technologies such as case-based reasoning, fuzzy reasoning and neural networks can be integrated to solve more challenging practical problems faced by the steel industry in the future. The trend of manpower getting more costly and computer becoming cheaper will result in further interest in the applications of fuzzy systems in future.

The number of fuzzy logic applications in iron and steel making is increasing rapidly due to its good controllability in systems where it is difficult to apply OR methods, traditional PID control and modern control theory based on process models. The contents of fuzzy systems are easily understood by operators as the empirical knowledge of operators is incorporated in the system in the form of rules. However to increase the scope of applications of fuzzy systems in iron and steel making in order to increase the productivity of development of fuzzy systems, and also to reduce the number of fuzzy systems which fail in meeting their targets, the following areas need to be given more attention and researched further.

- In expanding the fuzzy systems to complex large-scale process control, further research is to be carried out on the application of knowledge structuring and multistage fuzzy inference processes.

- Using fuzzy computers with high speed information processing which are still being developed, would be inevitable as the scope of applications is expanded in the future.

- Developing a method of estimating the CPU time and memory usage as well as the man power needed for fuzzy system development. Presently, due to the trial and error process of system development, it is very difficult to forecast these parameters accurately.

- Using neural networks or other means for automatic tuning of membership functions. When the operational conditions of a process change, the membership functions are required to be revised and currently this is being done by trial and error.

- Development of efficient fuzzy system building tools and tools for supporting the knowledge acquisition and knowledge representation. This would result in improved performance of fuzzy systems and increased productivity in developing fuzzy systems.

CHAPTER 3

CHAPTER 3

ELICITING KNOWLEDGE FOR MATERIAL DESIGN USING PAPER MODELS AND CODIFICATION SCHEME

3.1 INTRODUCTION

Expert system development for material design is a complex task, due to the difficulties faced in the knowledge elicitation process. This is because the design problems are ill structured, they are difficult to systematise, a large number of rules are involved, many complex factors interact, and customer requirements vary greatly. In addition, material design knowledge is held in largely intuitive undefined format. Another problem encountered in the material design process is that there is no linear relationship between various chemistries and process parameters. It is also the process of trading off some parameters, at the expense of some other parameters. For example, to increase the tensile strength higher carbon contents are required, but higher carbon content is not good for toughness and weldability. Most problems concerning unsuccessful developments of knowledge-based systems stem from non-technical issues such as cognitive and psychological problems rather than purely technical issues such as inference engine and expert system shells [80]. This chapter focuses on the human aspects and practical experience gained while developing material design knowledge-based system at BHP Steel is the basis for this chapter.

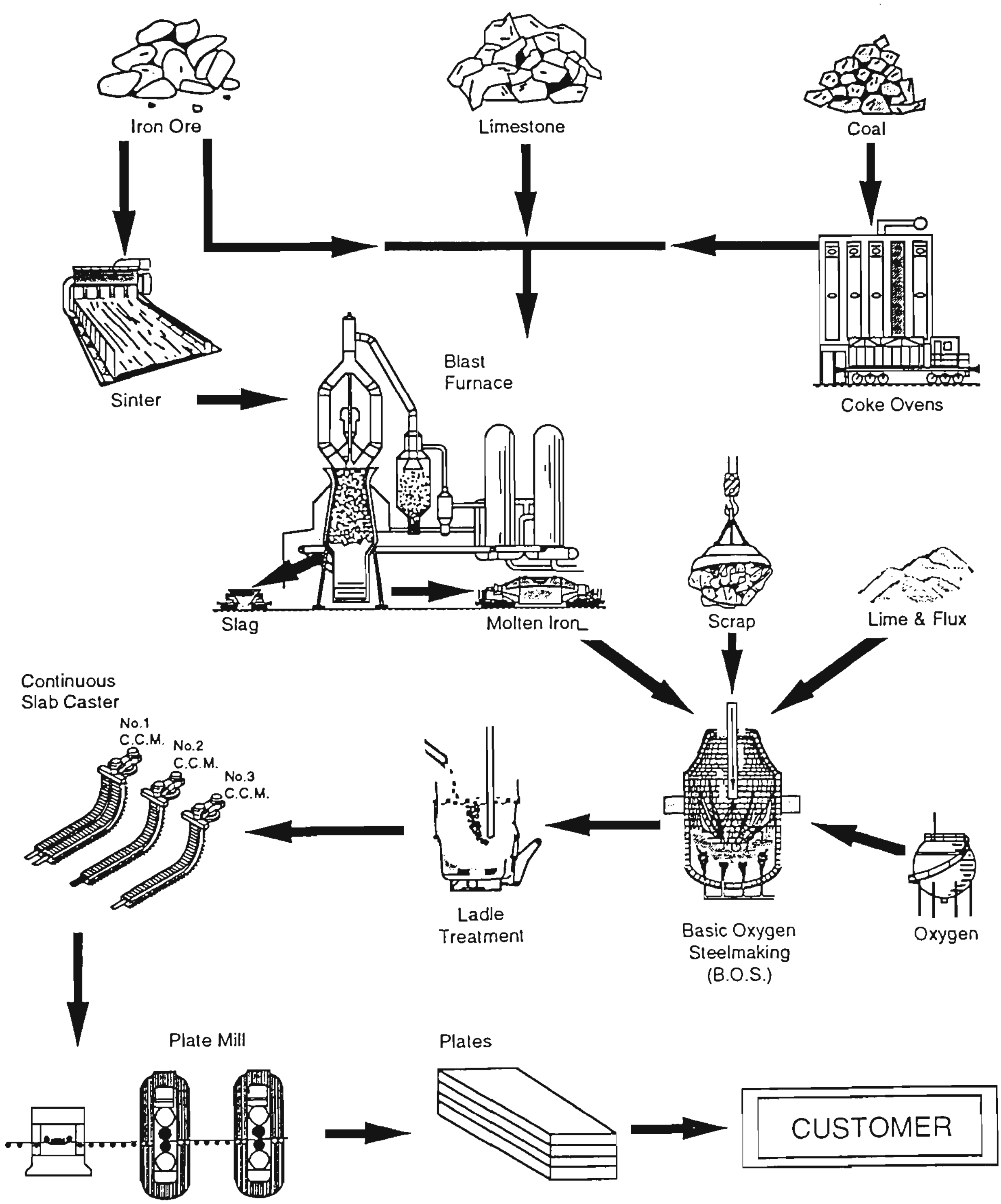


Figure 3.1 Major Steel Making Processes

Major processes involved in steel making are depicted in figure 3.1. Each process is controlled by various process parameters and these process parameters have complex inter-relationships which affect the material design. The term material design in this chapter therefore refers to not only the design of chemistry of the material, but also the design of various process parameters for the major processes involved in the production of steel plates which include BOS, ladle injection station, slab caster, and the plate mill. This implies that Knowledge Elicitation (KEL) is to be carried in both the chemistry and the processing domains.

Knowledge elicitation can be defined as the process of extracting knowledge, from the human domain experts, to be encoded in the knowledge-based system. The three main areas in the KEL are:

- Knowledge Collection
- Knowledge Analysis and
- Knowledge Representation

The knowledge collection process exercised so far is mainly through interviews with experts (both structured and unstructured), reading manuals and other documents, and by analysing past cases. The results of interviews are usually long transcript filled with messy knowledge. Knowledge analysis is applied to make sense of the knowledge thus collected. Analysing the knowledge consists usually of getting an intuitive feel for the subject and starting to find a workable structure [4]. Representing knowledge in both an understandable and a useable form is the most important stage in the KEL process. The purpose of styles of knowledge representation is principally to find a method of organising information in a manner which is conducive to human generation and review,

particularly during the conceptual stages of system development. Knowledge representation consists of translating declarative and procedural interpretations into a form that can be interpreted by a machine. Various knowledge representation techniques commonly used include production rules, frames, semantic networks, scripts, outlines, flow charts, example sets, repertory grids, object-oriented representations, and the use of tools developed for knowledge representation.

The knowledge collection is generally done utilising only one expert [6]. Using multiple experts is not usually considered because there is often only one expert readily available to participate in the project. However, to improve the efficiency of the knowledge engineering methodology, the use of second source of knowledge throughout the KEL process is advocated by Moore and Miles [54]. This approach eliminated the problems of inaccessibility of experts, chance of missing vital information and time-consuming KEL. This approach had some disadvantages also such as possibility of clashes of information, questioning the integrity of experts and covering the same ground twice. But these problems could be easily overcome by using a sensible approach and the benefits far outweigh the disadvantages. This approach of using multiple experts is utilised in the KEL process presented in this chapter. During the KEL process a number of experts in the steelmaking field from various departments including the product development and specifications section, the BOS, ladle injection station, continuous caster, plate mill as well as sales and marketing were consulted extensively. A total of 21 experts were consulted during various stages of the KEL process.

Agarwal and Tanniru, [107] describe the results of an experiment conducted to compare the unstructured knowledge acquisition interview with a specific type of structured knowledge acquisition interview. The objectives of this research are to develop a

meaningful structure for knowledge acquisition interview related to the acquisition of business knowledge and also to address the issues of the practical applicability of different types of interviews. A business decision-making activity is the domain model in this research and senior managers form industry was the subjects. The results indicate that the performance improves considerably with the structured interview method. The technique allowed novice knowledge engineers to perform at a level that was comparable to experienced knowledge engineers. The researchers have postulated the following hypothesis based on the experimental investigation:

- The structured interview technique is a more efficient procedure for extracting knowledge than the unstructured interviewing.

- The use of structured interviewing technique will allow novice knowledge engineers to perform better than they would using the unstructured interview.

- The structured interviewing technique will extract more subjective and qualitative knowledge form experts than the unstructured interview.

- The structured interviewing technique will provide the expert more assistance in recall and anticipation than the unstructured interviewing.

The limitations of this study include that the structured interview was used in only one specific resource allocation problem domain, and system analysts were used as surrogates for experienced knowledge engineers. Another main limitation of this work is that the investigation of the performance of the technique was undertaken in a single knowledge acquisition session. The performance of the technique in subsequent sessions

cannot be ascertained through this work. It would not be possible to ascertain the effectiveness of this technique throughout the development cycle of the expert system.

As described in this reference, unstructured interviews are beneficial in initial stages of the KEL to obtain background information regarding the knowledge bases involved in the design process. In the KEL methodology developed during the current research, unstructured interviews were utilised in the initial stages followed by several sessions of structured interviews.

Review of a class of knowledge acquisition tools that presuppose the problem-solving method, as well as the structure of the knowledge base has been described in [108]. These explicit problem-solving models are exploited by the tools during knowledge acquisition, knowledge generalisation, error checking and code generation.

Knowledge acquisition tools provide a high-level interface that abstracts from the implementation details of the expert system. In fact, some tools have sufficient knowledge of a domain to allow a domain expert to build a knowledge base without the assistance of a knowledge engineer. Furthermore, knowledge acquisition tools can facilitate maintenance by allowing easy access to a knowledge base for adding new and deleting outdated knowledge. The problem of communication gap between the knowledge engineer and the domain expert is eliminated through the use of these tools. Expert system developers, who do not have knowledge of the specialised languages that use nontraditional programming paradigms, could use these tools.

The six existing tools described in this study to demonstrate common characteristics are briefly described below.

MOLE is a tool for building diagnostic expert systems. A mole-generated expert system asks the user about the symptoms that are present and proposes a set of alternatives or explanations for each symptom. It then queries the user about information that will help to differentiate these alternatives.

BURN builds expert systems that reason quantitatively and use a case-based reasoning method to solve sizing problems such as the sizing requirements for a computer system. A Burn-generated expert system elicits information about a particular sizing problem from the user. It then identifies other, similar, already solved problems in a knowledge base of cases and uses the differences between the solved and unsolved cases to extrapolate from a known solution to a new one.

SALT builds expert systems that perform constraint-satisfaction tasks such as configuring an elevator system or scheduling tasks in an engineering department. A Salt-generated expert system constructs an approximate plan or design by proposing a value for one parameter of the design at a time. It then checks whether each parameter satisfies all constraints on it, and revises past decisions whenever constraint violations are detected.

CGEN constructs expert systems for hierarchical configuration tasks, where it is necessary to choose appropriate components and structures to integrate those components. CGEN-generated expert system queries the user for functional, cost and performance goals of the system to be designed. These specifications are then refined using a hierarchical, stepwise-refinement process. In this process, user-given specifications are decomposed successively until components can be selected from a library, and appropriate structures are selected to integrate these components.

KNACK generates expert system that assist a user in gathering information form a variety of sources, and in combining that information into a document, e.g., writing proposals and documenting design decisions. A knack-generated expert system identifies all pieces of information that are appropriate to acquire. It then selects one piece of information and a strategy for acquiring it and applies the selected strategy. Integrating that information with whatever information it already has is then undertaken. A knack-generated expert system produces a report documenting the acquired information.

OPAL is a tool for building expert systems that perform skeletel-paln refinement tasks, e.g., assisting physicians with the treatment according to protocols of patients who have cancer. An Opal-generated expert system follows the procedures specified in a standard plan and specialises that plan with parameters that are specific to the current case. It then modifies the plan periodically in response to the observed patient reactions to the earlier actions.

The two main disadvantages of these tools are that it is difficult to determine whether a tool is appropriate for the given application and that the tools break down once they encounter situations that cannot be solved by their presupposed-problem solving methods and accompanying knowledge representations.

Another requirement for utilising the tools is that they are useful in extending the knowledge bases, which are already existing. In the present case the knowledge base was developed from scratch and hence it was not possible to use these tools in the development of the knowledge bases.

The most important requirement to utilise these tools is that the problem solving methodology should be known before commencing KEL. In the present research the problem solving methodology was initially not known due to the complex nature of the problem of determining steelmaking aim chemistries. The KEL process was commenced with an aim to first develop a methodology for the hybrid knowledge based system. Due to this reason it was not feasible to commence the KEL utilising tools available to assist in this process such as the one described in this reference.

Jones *et. al* [110] describe the analysis of the raw data that has been extracted from the experts, with an aim to eliminate unnecessary detail from interview transcripts to enable focusing upon the more relevant data. This was achieved through a simple technique based upon cheap and readily available technology. This approach is expected to convert speech from the experts into production rules, or into a frame or network representation. The research instrument used in the analysis of the elicited data was a wordprocessor using Microsoftword software. In addition to providing a standardised approach to the initial data reduction stages of transcript analysis, the research also tries to eliminate wherever possible, the need for subjective judgement of the knowledge engineer during early stages of the analysis process.

The paper emphasised how several notions including those of domain concepts, inquiry terms and focal sentences, may be utilised in order to assist in the standardisation aspects of qualitative analysis. It is claimed that the major strengths of the method are its ability to minimise the need for subjective interpretation and its effectiveness in eliminating unwanted material. However, this is only a small-scale case study and the methodology requires further testing on different domains and expert sources to ascertain its usefulness.

The KEL methodology proposed by Trimble [88] consists of the following steps:

- One or two unstructured interviews
- Case histories and broadly focussed interviews
- Narrowly focussed interviews
- Prototyping and iteration

Most KEL processes follow this methodology or a slight variation of this. If this approach is applied to the material design problem it results in less knowledge acquired in spite of several KEL sessions. The problem faced by the knowledge engineer is that structured interviews are unable to produce the expected knowledge, as the experts could not recollect all the relevant aspects, during a particular session of the interview. This is due to the fact that the material design problems are so ill structured and a large number of rules are involved with complex interrelationships. Even while analysing the past cases, it is observed that the experts are some times at loss to remember exactly why the particular decision was taken. The decision might have been taken based on discussions with experts in other related areas such as the BOS, ladle injection station, slab caster, and plate mill. The interviews were not leading towards collection of sufficient knowledge for the development of first prototype of the knowledge-based system, in spite of the cooperation from the experts and their willingness to share the knowledge they have possessed over a long period of time.

Zaff *et. al* [105] have expressed the limitations of the KEL within the confines of a verbal discourse. According to them, in this situation the expert is forced to rely exclusively upon mental stimulation which can severely curtail the amount and accuracy

of the information elicited. The vocabulary initially used by the expert to talk about the domain with a novice is often inadequate for problem solving [22].

Case Based Reasoning (CBR) means using old experiences to understand and solve new problems [38]. In CBR, a reasoner remembers a previous situation similar to the current one and uses that to solve the new problems. CBR can mean adapting old solutions to meet new situations; using old cases to critique new solutions; or reasoning from precedents to interpret a new situation or create an equitable solution to a new problem.

ID3, C4 and C4.5 are inductive inference tools used for acquiring knowledge from large volumes of messy, real world data [69], [111]. Utilising these tools, decision trees can be constructed from objects described in terms of a fixed set of attributes. C4 is capable of dealing with cotinuous or discrete attributes, noisy data and missing attribute values. The pruning algorithm based on C4 dramatically improves the simplicity and consequent intelligibility of the derived rules. C4.5 which is a descendent of ID3 [69] is based on constructing a model inductively by generalising from specific examples, utilising numerous recorded classifications.

One of the main requirements in this inductive approach is that sufficient data is required. Inductive generalisations proceeds by identifying patterns in data based on some statistical tests. The amount of data required is affected by factors such as the numbers of properties and classes and the complexity of the classification model. Usually, the construction of a reliable model requires hundreds or even thousands of training cases. Induction on previous decisions by experts was also considered as an alternative method of knowledge-base development. The number of training cases

available in the field of material design in steel making is too small and hence this inductive learning technique is not suitable for KEL in this domain.

The process of eliciting knowledge from human experts by interviewing has a major disadvantage that the experts are often unable to articulate their reasoning rules. The inductive learning approach that induces knowledge from a set of training cases is not effective if the number of training cases is not large enough. The approach put forward by Jang *et. al* [109] tries to combine the strengths of the above methods to compensate for their weaknesses. In this approach, human experts are responsible for solving problems, where as an inductive learning algorithm is responsible for reasoning and consistency checking.

The system developed has been implemented in learning geometric patterns and blackjack game strategies. A modifying algorithm for inductive learning is designed so that an expert communicates with the system in an interrogative style during the inductive process. After a knowledge structure is induced from its training cases, the algorithm identifies cases that cannot be correctly classified. These cases are brought to the expert in the form of questions to be solved. Once they are solved, they become new training cases to the inductive algorithm for further training. In this way, expert knowledge is incrementally elicited and incorporated into the induced knowledge structure. The six phases of the interactive induction include, rule description, case induction, contradiction identification, revision and augmentation, local refinement and result validation. Inductive inference tool ID3 has been utilised in this research.

In steel making, due to the improvements in processing and due to introduction of new techniques and equipment, the previous decisions cannot always be applied to new

cases. In addition, the previous decisions also depend on the plant situation at that time. Empirical models utilised in the material design system explained in the next chapter, are based on the grade history database. This database is updated periodically to include latest data about the performance of various grades of steel plates. This results in the empirical models being revised periodically and hence the results obtained would vary over a period of time. Due to these drawbacks, the inductive learning technique was not applied in the development of the knowledge-bases.

The KEL approach advocated in this chapter attempts to eliminate the above mentioned problems, by utilising a codification scheme, along with paper models. Paper models are considered as tried, trusted and low tech tools. The details of implementation of paper models and their advantages in validating, verifying, and testing knowledge-bases are well described in the literature [46]. In this chapter they have been utilised as a suitable vehicle to make an explicit mapping from the elements in the knowledge domain and their interrelationships. The knowledge engineer develops a set of conceptual models on paper, based on the results of the structured and unstructured interviews. In this chapter customer special requirements are codified through a three character codification scheme having hybrid type structure based on the initial unstructured and structured interviews. The chapter also advocates the use of non-interview techniques to collect the expert knowledge to reduce the expensive interview time. The next stage of KEL proceeds to elicit knowledge corresponding to the customer special requirements. Use of paper models improves the efficiency of KEL by offering clarity of expression and building firmer consensus among experts, which results in elimination of errors. The codification scheme along with the knowledge representation utilising the tool TABLEAUX results in reduced search time and storage space, in addition to simplifying the knowledge representation.

3.2 CODIFICATION SCHEME

Initially in the unstructured interviews, general knowledge about the material design process is extracted, which gives a broad view of the knowledge required for the design process. Here, it becomes apparent that the main factors effecting the material design are:

- Chemistry
- Processing
- Mechanical Properties
- Testing Requirements

The unstructured interview session also outlines the requirement of the system and informs what the expert is expected to contribute. This is followed by structured interviews which give an idea of the various major knowledge sources which are to be further probed to obtain the knowledge required to deal with the design problems. Figure 3.2 depicts the knowledge sources identified based on the customer special requirements.

The next step is to identify the subgroups associated with the knowledge sources. Further structured interviews resulted in the identification of these sub groups. Examples of the subgroups associated with the charpy testing knowledge source include:

- Structural Steel (AS3678)
- Structural Steel (JIS3106)
- Pressure Vessel Steel (AS1548)
- Pressure Vessel Steel (ASTM A516) etc.

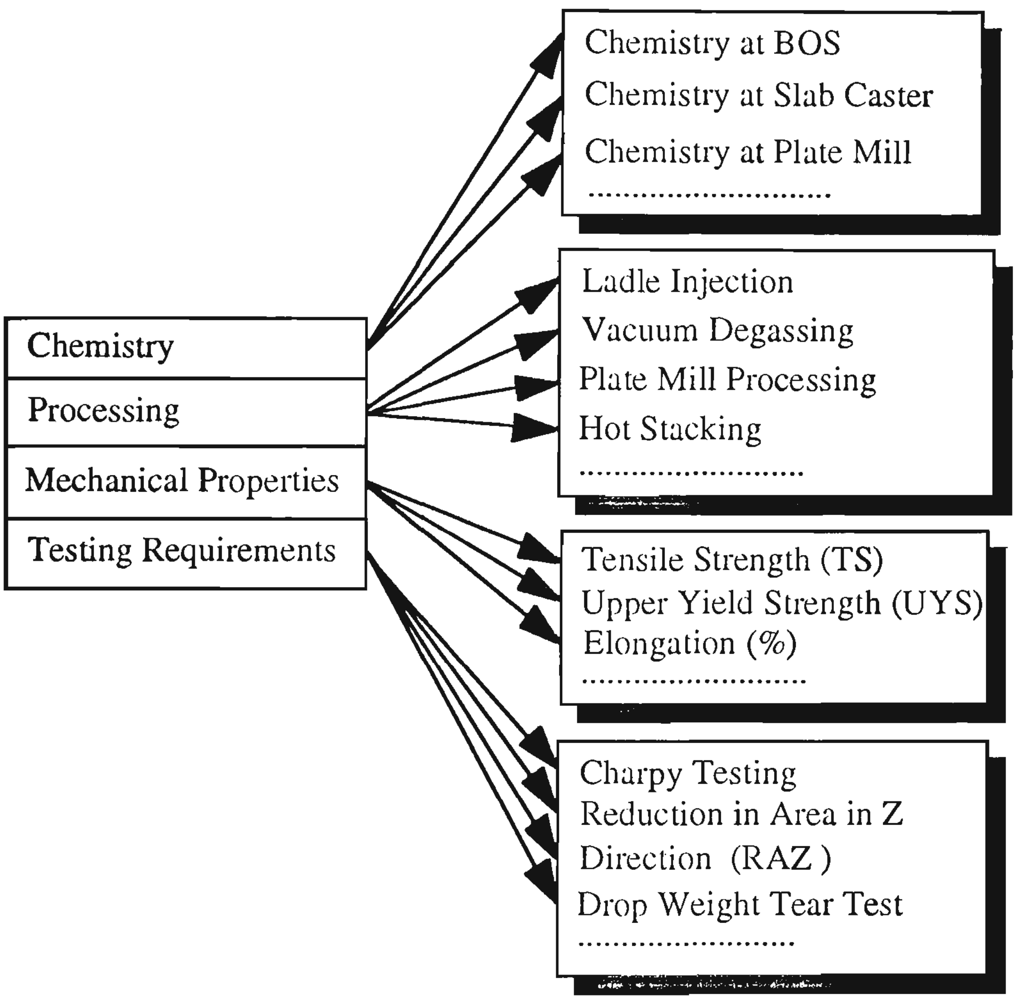


Figure 3.2 Main Factors in Material Design and Corresponding Sample Knowledge Sources

It becomes apparent at this stage about the main knowledge sources and the sub groups associated with these knowledge sources based on the customer special requirements.

The customer special requirements based on the unstructured and structured interviews, were codified into three character codes with hybrid type code structure, given by the equation

$$\text{Customer Special Requirement Code} = X_i Y_j Z_k \tag{3.1}$$

The first character in the code is X_i which is the ith property of the steel grade and i = 1, 2,.....L represents L properties of the steel such as tensile strength, yield strength, elongation, etc. The first character indicates the major codes corresponding to the knowledge sources.

The second character in the code is Y_j which is the jth type of steel and j = 1, 2,.....M represents M types of steel such as structural steel, pressure vessel steel, line pipe steel, etc. The second character in the code indicates the sub groups of the knowledge sources.

These two codes are not sufficient to describe the customer special requirements fully. A third character is required to indicate the actual values of the properties corresponding to any combination of the first two characters, therefore Z_k is introduced in equation 3.1. Z_k is the kth value of the ith property of steel and jth type of steel, and k = 1, 2,... N represents N actual values of the properties relating to each combination of X_i's and Y_j's. Furthermore, Z_k has a hierarchical structure as compared to X_i's and Y_j's which have chain type structure.

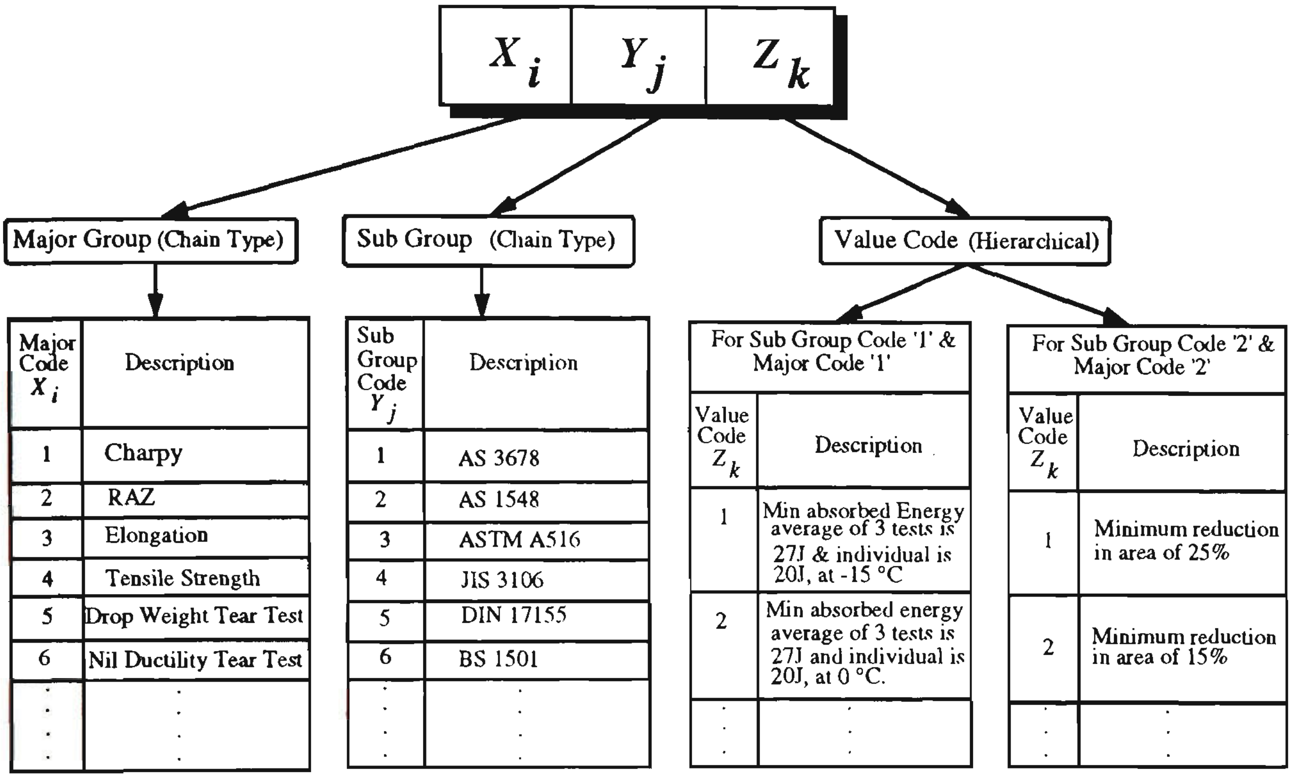


Figure 3.3 Codification Scheme for Customer Requirements

Figure 3.3 above illustrates this codification scheme along with major codes, sub group codes and the corresponding value codes. Using upper case letters (26), lower case letters (26) and decimal digits (10), a total of 62 values for each of the characters in the code is possible, which means that a total of $(62)^3$ or 238328 customer requirement codes are possible in this scheme.

The codification scheme described here is a combination of the chain-type and hierarchical code structure. The chain-type structure facilitates vertical (depth first) search and the hierarchical type structure assists in the horizontal search. The significance of using these codes is that the knowledge representation becomes simple and less time consuming. This also helps in organising knowledge into appropriate knowledge sources. Corresponding to these codes the rules are formulated based on the

knowledge extracted in the knowledge collection phase. The following case study would illustrate this concept more clearly.

To codify customer requirement of charpy testing for structural type (AS3678) steel at -15 °C with minimum absorbed energy average of 3 tests 27J and individual 20J, the values from the table in figure 3.3 are substituted into equation 3.1, ie.

$$X_i = 1, \quad Y_j = 1, \quad Z_k = 1$$

Thus the customer requirement code for the above illustration is "111". Similarly all customer requirements could be codified by substituting corresponding values of X_i's, Y_j's and Z_k's obtained from figure 3.3 into equation 3.1.

Table 3.1 Customer Requirement Codes

CUSTOMER REQUIREMENTS	CODES
Charpy testing for AS3678 (Structural) Steel at 0 °C with minimum absorbed energy average of 3 tests 27J and individual 20J.	112
Charpy testing for AS3678 (Structural) Steel at -15 °C with minimum absorbed energy average of 3 tests 27J and individual 20J.	111
Charpy testing for JIS3106 (Structural) Steel at 0 °C with minimum absorbed energy average of 3 tests 47J.	141
Charpy testing for JIS3106 (Structural) Steel at -5 °C with minimum absorbed energy average of 3 tests 47J.	142
• • • •	• • • •

Once all the customer requirements based on the initial unstructured and structured interviews are thus codified, the further knowledge collection could proceed smoothly as now knowledge can be extracted corresponding to the special requirements codes only, by using the new methodology to be explained later. This gives an exact direction in which the knowledge collection can proceed. Table 3.1 depicts some of the sample customer requirement codes corresponding to the testing requirements.

3.2.1 Benefits from the Codification Scheme

Material design knowledge as explained in section 3.1, is characterised by a large number of rules including expert rules as well as rules based on the intuition and heuristic knowledge of experts. Representing this large number of rules cannot be accomplished if an appropriate codification scheme is not developed. Because of the hierarchical structure of the codes in the codification scheme and due to the use of alphabets (both upper and lower case) along with decimal digits, a large number of rules (over 230,000) could be represented in the material design system. Thus the codification scheme presents a simplified hierarchical structure to represent the material design knowledge.

The codification scheme also helps in reducing the computer search time, because the first character in the code directs the search to take place in a particular knowledge source among the 50 knowledge sources present in the system. In addition, the codification scheme also reduces the storage space required in representing the knowledge rules as explained in section 3.5.

Facilitating simplification in representing large knowledge-bases and reducing computer storage space as well as the search time are the two important benefits of the codification scheme explained above. However, there is another important dimension of facilitating the development of a user friendly Graphical User Interface (GUI) with the utilisation of this codification scheme. Without the aid of this codification scheme, developing the GUI which enables input of a large number of customer special requirements in a simplified manner cannot be achieved. The development of the GUI aided by this codification scheme is described in chapter 6.

3.3 NON-INTERVIEW TECHNIQUES

The most common technique for building the knowledge-base is interviewing, which has been criticised as an unstructured process, difficult, tiring, unscientific, yet very critical [21]. The interview process is also very expensive, due to the experts being highly paid, and due to their unavailability. The material design knowledge as depicted in figure 3.4, constitutes two main types of knowledge viz.,

- Expert Knowledge, and
- Heuristic Knowledge

The expert knowledge is usually available in the form of written information such as technical reports, research papers, guidelines, text books, manuals, standard procedures, material standards, memos, letters, reply to customer technical enquires, diagrams, graphs, formulae, tables, flow charts, etc. The above sources of expert knowledge could be collected without much intervention of the experts and this results in considerable savings in expensive interview time. However, to identify the above

sources, initial unstructured interviews are essential. Thus the approach used in this work places more emphasis on the above sources to collect the expert knowledge. After collecting these and analysing, it is again necessary to conduct structured interviews to clarify any ambiguities, missing links, or inconsistencies. Another advantage of the non-interview techniques is that the dilution of the knowledge or the possible distortion of the knowledge while flowing verbally from the experts to the knowledge engineer is also fully eliminated.

The heuristic knowledge component of the material design knowledge is more suited to be collected mainly based on interviews, as this type of knowledge is based on the intuition of the experts and thumb rules. Figure 3.4 illustrates the main process of collecting both the expert and the heuristic knowledge components.

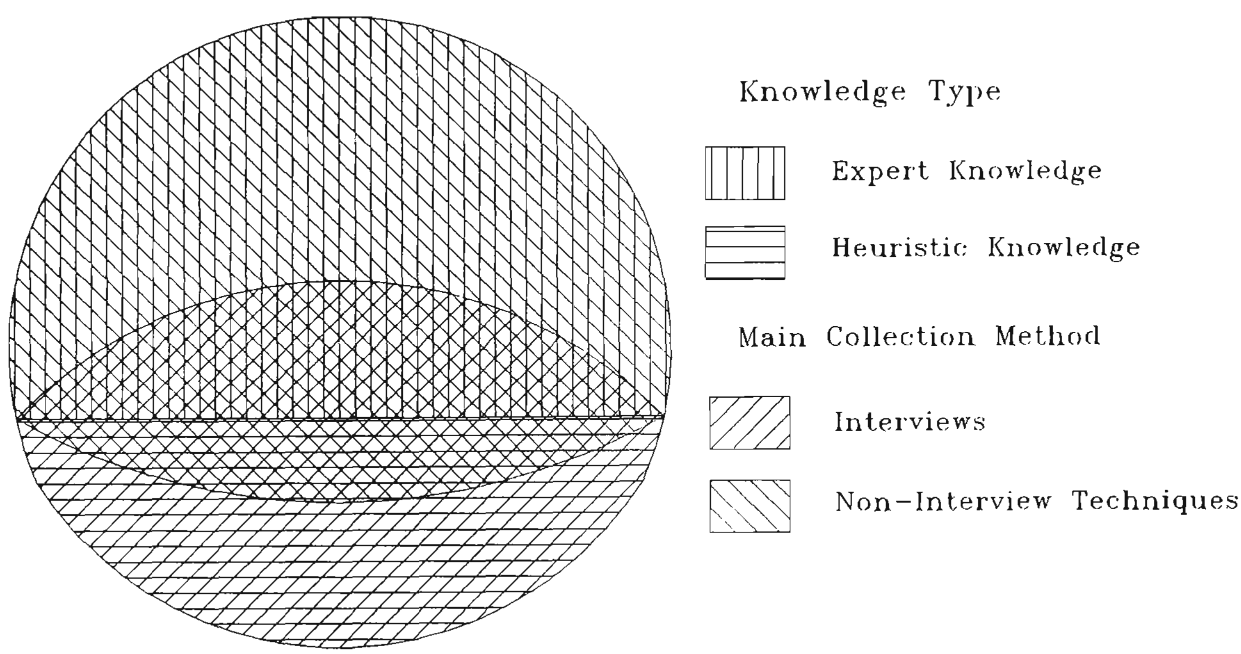


Figure 3.4 Material Design Knowledge

3.4 PAPER MODELS

Paper models are prepared by the knowledge engineer after analysing the results of interviews during the KEL. These contain the interpretation drawn from the interviews in the form of papers, free from computer jargon and which is readily understandable to the experts. These models are used as the primary resource for the next meeting with the experts. The following example illustrates the usefulness of the paper models more clearly. The flow chart in figure 3.5 is the result of first round of structured interviews which depict the basic approach to the material design system. This flow chart was prepared after separate structured interviews with six expert metallurgists and then given to all the six experts for review.

Second round of structured interviews were then conducted, in which all the six experts participated. Ambiguities, inconsistencies or omissions in the initial paper model were pointed out by the knowledge engineer and clarifications were offered by the experts to support their view point. Experts participated in a discussion to justify their approach, when clarifications were sought. It was found during the second round of structured interviews that this paper model was far from complete and unacceptable to the experts. It was suggested that the input to the system about the end use of the steel required should be at the beginning rather than at the end as shown in the flow chart of figure 3.5. The conflicts which were present at the beginning of the interview session were resolved at the end of the session and overall consensus reached mainly due to the coordination among the experts and their impartial opinion.

There are two empirical models utilised in the design process. Model I depicts the relationship between the Carbon Equivalents (CEQs) and the steelmaking aim

chemistry. Model II is developed by using a huge database having performance data about all the steel grades produced in the past. Model II could be used in the prediction of tensile strength and yield strength based on the steelmaking aim chemistry. It was also suggested that Model I should not be used for iterations as it has less accuracy of the order of about ±20MPa in the prediction of tensile strength and yield strength. Instead, this model should be used to check whether the mechanical properties are achievable. It was also pointed out by an expert that Model II is more suitable for the iterative process. A safety margin of 40 MPa was added to the required tensile strength and upper yield strength to take account of the error in model I during the checking process.

These modifications were incorporated in the revised flow chart shown in figure 3.6 and again circulated to all the experts concerned for review and validation. This flow chart (final paper model) was acceptable to all the experts and this formed the basic approach to the development of the material design system.

In the flow charts in figure 3.5 and 3.6 CEQ, CTS, CYS, RTS, RYS refers to carbon equivalent, computed tensile strength, computed yield strength, required tensile strength and required yield strength respectively. KB I, KB II, KB III and KB IV are the four knowledge-bases utilised in the material design system.

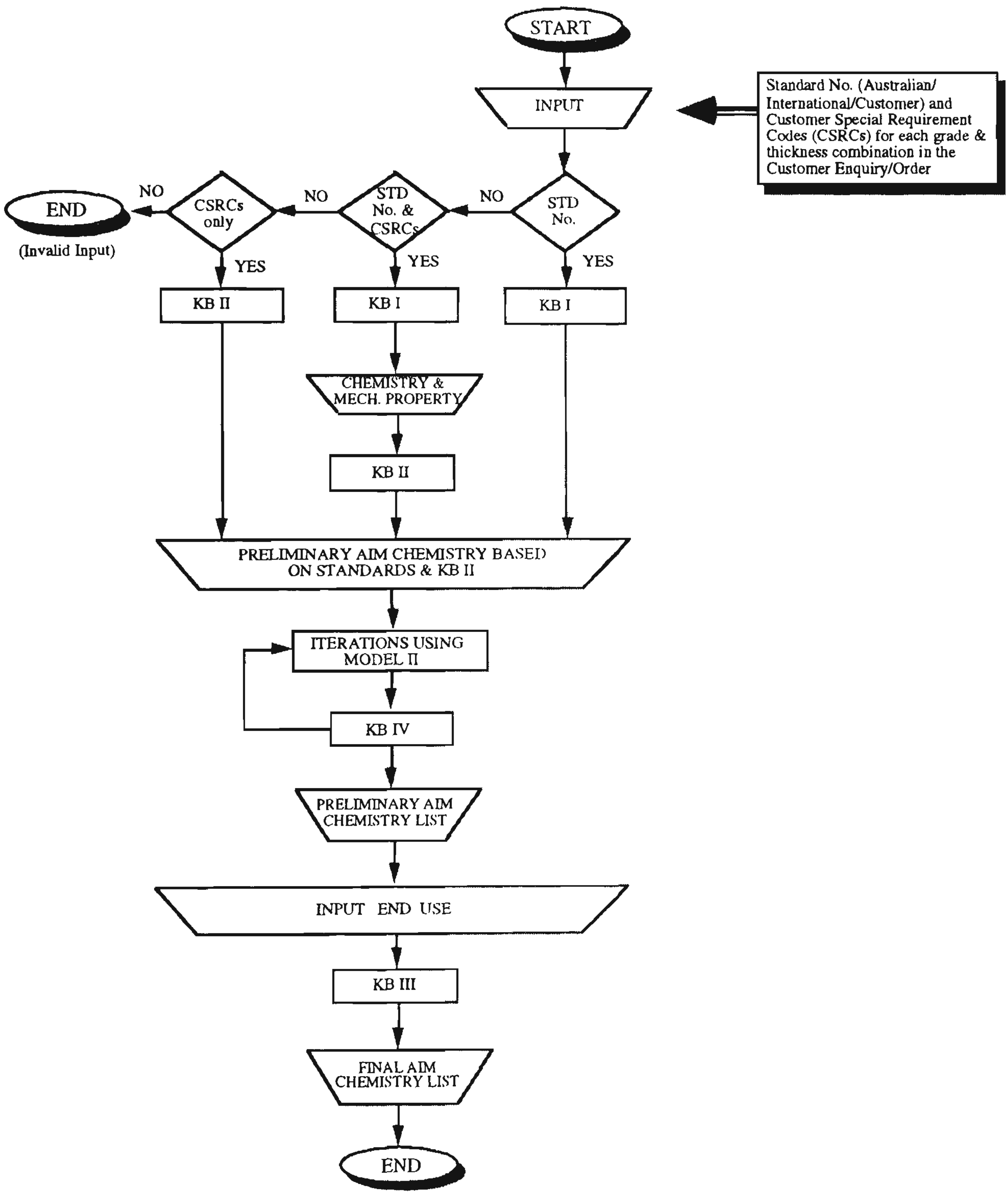


Figure 3.5 Initial Flow Chart for Material Design

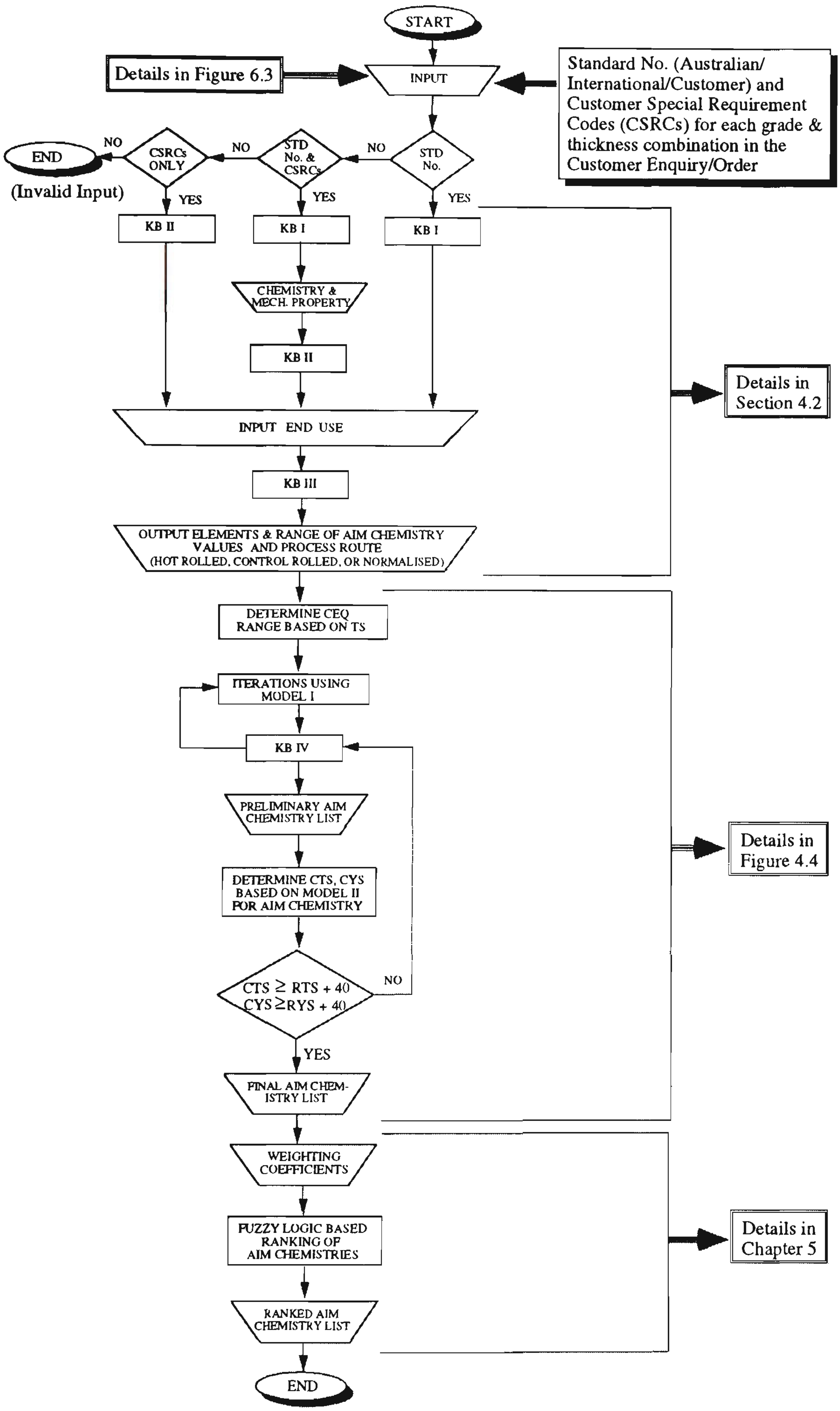


Figure 3.6 Revised Flow Chart for Material Design

3.5 KNOWLEDGE REPRESENTATION

The purpose of knowledge representation is to support the processing required to arrive at a conclusion or to provide options for selecting a solution. Knowledge representation which is the most difficult yet important stage in KEL has emerged as one of the fundamental topics in artificial intelligence research. Knowledge representation in this research has been carried out utilising the knowledge representation tool TABLEAUX [44]. This is a decision table based tool to assist in organising and representing knowledge for incorporation within knowledge-based systems. General capabilities offered by conventional expert system tools fall behind the needs of a clear representation of design problems [27]. But in TABLEAUX when the knowledge-base becomes very large with many complex inter-relationships, a visually more powerful aid for detecting inconsistencies, ambiguities and omissions is provided. Implementation of the knowledge-base built using TABLEAUX can be achieved directly through program calls to the inferencing facilities within TABLEAUX. Using TABLEAUX enables the representation of knowledge in a tabular form, which is especially useful for a large number of rules with complex interrelationships.

Knowledge analysis which is a pre-requisite to knowledge representation, is undertaken to convert the results of the interviews into rules to enable representation in the rule base. The knowledge is compiled and classified into appropriate categories corresponding to the knowledge sources. This knowledge was first represented in the form of IF - THEN rules, and belonged to two main groups viz. Chemistry and Processing. An example in the category of chemistry included:

IF	Type of steel is structural,	and
	Testing requested is RAZ,	and
	Value of RAZ is 25% minimum	
THEN	Maximum Sulphur is 0.005%,	and
	Maximum Hydrogen is 0.00019%,	and
	Maximum Calcium is 0.010%	

Similarly, an example of rules for the processing category included:

IF	Type of steel is structural,	and
	Testing requested is RAZ,	and
	Value of RAZ is 25% minimum	
THEN	Critical caster alignment is A1,	and
	Electro-magnetic stirring code is E4,	and
	Sulphur print requirement is 1,	and
	Vacuum degassing code is H	

This formulation of rules based on the knowledge collected using the new KEL approach, became the basis for the knowledge representation illustrated below.

Examples of knowledge representation using TABLEAUX corresponding to appropriate customer requirements are depicted in figure 3.7, which shows the knowledge representation before the codification of the customer requirements. Simplification of knowledge representation and saving in storage space and search time with the use of codification scheme is illustrated in figure 3.8, for the same examples explained earlier. The benefits of representing knowledge by codifying the customer requirements could be significant because the material design system consists of several thousands of rules.

<table>
<tr><th></th><th>Steel Type</th><th>Testing</th><th>Value</th><th>Max Sulphur</th><th>Max H</th><th>Max Ca</th></tr>
<tr><td>Rule 1</td><td rowspan="2">Struc-tural</td><td rowspan="2">RAZ</td><td>25% Min</td><td>0.005%</td><td rowspan="2">19 ppm</td><td rowspan="2">0.01%</td></tr>
<tr><td>Rule 2</td><td>15% Min</td><td>0.008%</td></tr>
</table>

<table>
<tr><th></th><th>Steel Type</th><th>Testing</th><th>Value</th><th>Align-ment</th><th>EMS</th><th>Sulphur Print</th></tr>
<tr><td>Rule 1</td><td rowspan="2">Struc-tural</td><td rowspan="2">RAZ</td><td>25% Min</td><td rowspan="2">A1</td><td rowspan="2">E4</td><td rowspan="2">1</td></tr>
<tr><td>Rule 2</td><td>15% Min</td></tr>
</table>

Figure 3.7 Knowledge Representation in Tableaux Before Codification

	CSR Codes	Max Sulphur	Max H	Max Ca
Rule 1	211	0.005%	19 ppm	0.01%
Rule 2	212	0.008%		

	CSR Codes	Align-ment	EMS	Sulphur Print
Rule 1	211	A1	E4	1
Rule 2	212			

Figure 3.8 Knowledge Representation in Tableaux After Codification

3.6 SUMMARY AND CONCLUDING REMARKS

A methodology which utilises a three character codification scheme has been developed to deal with the complex task of KEL in the development of a knowledge-based system for material design. In the field of material design characterised by a large number of rules with complex interrelationships, the methodology adopted in this work simplifies the KEL process by giving a definite direction to the KEL process.

The procedure involved in this approach is to identify the possible customer requirements with regard to chemistry, processing, mechanical properties, and testing requirements, then to codify them and finally to direct the KEL to acquire knowledge to deal with these customer special requirements. This approach proves to be very

beneficial in eliciting all the relevant information and continuing KEL in the right direction. The codification scheme proposed is very useful in reducing the computer storage and search time considerably and hence simplifying the knowledge representation.

Use of paper models is advocated to improve the efficiency of KEL process, as such a model offers easy portability, accessibility to the non-computer user and clarity of expression. Paper modelling approach is more suited for developing knowledge-base involving multiple experts as it builds firmer consensus and results in the elimination of errors. The importance of using the non-interview techniques is emphasised in this chapter aiming at efficiently collecting the expert knowledge by reducing the expensive interview time. The methodology presented in this chapter is based on the experience gained by the author in developing the material design knowledge-based system at BHP Steel of Australia. The speed of the KEL process increased enormously after the new methodology was introduced. The TABLEAUX tool proved to be especially useful in representing the knowledge in the tabular form corresponding to the special customer requirements.

The knowledge-base developed using the new KEL approach includes the rules regarding the chemistry and processing domains corresponding to the design of steel plates. This knowledge-base could also be utilised with appropriate additions and modifications, in the development of knowledge-based systems for the control of other areas in steel making such as BOS, slab caster and plate mill.

Integration of the codification scheme into the KEL process has the advantage that all the material design knowledge could be elicited and organised in a hierarchical structure

corresponding to the three character customer special requirement codes, which makes the development of the knowledge-based system much simpler and less time consuming. The main disadvantage of the KEL process described in this chapter is that the knowledge engineer's task becomes more demanding due to the additional load of preparation of the paper models and due to the iterative nature of paper modelling approach. However this disadvantage is largely off set by overall increase in the speed of the KEL process due to the introduction of paper models and is especially useful in developing knowledge-bases involving multiple experts where reaching consensus is very critical.

CHAPTER 4

CHAPTER 4

DETERMINING STEELMAKING AIM CHEMISTRY UTILISING ITERATIVE AND KNOWLEDGE-BASED APPROACHES

4.1 INTRODUCTION

Application of knowledge-based approach to steel material design is not new and some systems have been developed. Vasko *et. al* discuss the grade assignment problem [91-92], [97-98] which is an approach to optimally assign metallurgical grades to customer orders using fuzzy set concepts, a combinatorial optimisation formulation, and a heuristic solution procedure. The metallurgical grade assignment expert system utilises metallurgical expertise and statistically derived predictive equations along with characteristics and past performance of all the grades to generate a list of all applicable grades which satisfy the customer specifications. Ranking of various applicable grades and optimisation to minimise the number of grades and to maximise the likelihood that the customer specifications will be satisfied without difficulty is discussed in detail in these references. There is no description of how the list of applicable grades is generated by the expert system. The knowledge elicitation aspect of the expert system is also not described.

Yasuda *et. al* [100] have developed an expert system for the design of large diameter steel pipes. In their work a knowledge-base and a database containing past production results are used to design steel pipes. The system enables design of chemical

composition, forming and heat treatment conditions, and instructions for production processes. A method similar to hill climbing optimisation method along with expert knowledge is utilised in the system. It is claimed that the system is simple and even a beginner can design a material in about 10-30 minutes. The system is developed for designing large diameter steel pipes only and it is not described whether this could be used for other steel products. The KEL aspect including knowledge representation is not discussed in this reference.

Watanabe *et. al* [95] have briefly discussed the application of higher order reasoning techniques such as case-based reasoning, neural network reasoning, fuzzy reasoning and hypothetical reasoning, in the development of material design expert system at Nippon Steel. The main objective of the system is to perform manufacturability study utilising various reasoning functions. Hypothetical reasoning is utilised for the design of chemical composition where the candidate chemical compositions are checked against specific design conditions. But it is not explained how the initial candidate chemical compositions are obtained.

Trimberger and Hathaway [87] have described the development of an alloy melting expert system to select the furnace, crucible, mould(s) and raw material. The system generates specific instructions for each alloy mainly by utilising knowledge-based approach. Raw material selection involves choosing the individual metallic elements that will make up the alloy and calculating their proper weights. This module also utilises knowledge-based approach along with database of raw material.

In [87], [95] and [100], the emphasis is on the expert system aspect of material design, and the mathematical approach is not explained. This chapter discusses the first stage

of material design, which deals with the design of the steelmaking aim chemistry. The process of determining the steelmaking aim chemistry is treated in this chapter as a process which utilises both mathematical and knowledge-based approaches. In a manual design system, it is not possible to consider all combinations of various elements within the range of acceptable values, because of the enormous computations involved and thus the design may not be an optimum one. The system discussed in this chapter considers all the possible combinations and hence is expected to produce a better design than produced by experts with manual computations.

The tendency to crack in the Heat Affected Zone (HAZ) increases as the carbon and alloying element content increases. CEQ formula converts the greatly variable amounts of alloys in various steels in terms of a simple carbon steel. Thus CEQ gives an indication of tendency to crack. The mathematical approach involves iterations by using empirical models of the relationship between the CEQ and the chemistry. If an attempt is made to determine the chemistry based on the iterative process alone, the results obtained would not be realistic because the relationship between the mechanical properties and the chemistry is not always linear. In addition to this many complex factors interact in the material design process. All of these make it desirable to combine mathematical algorithms with the knowledge-based approach, which involves the application of the expert knowledge of metallurgists, and the heuristic knowledge including rules of thumb. The knowledge elicitation technique utilised in the development of knowledge-bases is discussed in the previous chapter, which gives more importance to non-interview techniques to reduce the expensive interview time. The knowledge elicitation is also characterised by a three-character codification scheme to codify all the customer special requirements based on structured and unstructured interviews. This codification scheme along with the use of knowledge

representation tool TABLEAUX [44] has resulted in reduced computer storage space and search time and hence simplifying the knowledge representation. TABLEAUX is a decision table based knowledge representation tool to organise and represent knowledge for incorporation within knowledge-based systems. This tool has proved to be very useful in representing large knowledge-bases with many complex interrelationships and facilitated easy maintenance of the knowledge-bases by the users as the knowledge-bases reside outside the source code. This hybrid approach is characterised by the application of the expert and heuristic knowledge at every stage of the material design.

The material design system was developed in C language on an IBM PC in Windows environment. The knowledge representation tool TABLEAUX is interfaced with the system. This enables access to the knowledge-bases and retrieval of the decisions from the TABLEAUX, while the system is executing the main program. The user interface was developed utilising a commercial package viz. PROTOGEN+, to make the system more user friendly.

4.2 ORGANISATION OF KNOWLEDGE-BASES

The knowledge required in the material design system consists of the expert knowledge of the metallurgists, the process knowledge and the heuristic knowledge, based on the rules of thumb and the intuition of the experts. All the above types of knowledge are organised into four knowledge-bases which are accessed at various stages of the design process. The knowledge-bases have two modules, one for the knowledge rules and the other for the databases. The knowledge-bases are organised in an order in which they are required in the material design. For example the first knowledge-base (KB I) is

Table 4.1 Examples of Rules in the Knowledge-Bases

Type of Rules	**Sample Rules**	**KEL Method**
Heuristic	$CEQ1_{max} = CEQ1_{min} + 0.08$ Calculated Tensile Strength >= Required Tensile Strength + 40 MPa $C_{sac} = C_{sac} + 0.005\%$	Interviews
Expert	If CSRC = 212 Then $S_{max} = 0.008\%$ If RAZ required > 15% Then $S_{max} = 0.005\%$ Titanium to Nitrogen Ratio = 3.42 Manganese to Carbon Ratio > 3.0	Interviews/ Non-Interview
Data	If Grade = AS3678-250-L15 and Test Piece Size <= 10x10mm Then Average Energy = 27J and Individual Energy = 20J If Grade = AS3678-250 and Thickness <= 8 mm Then Lower Yield Strength = 280 MPa, Lower Tensile Strength = 410 MPa and Lower Elongation = 22% If Grade is AS3678-250 Then $C_{max} = 0.15\%$ $Si_{max} = 0.35\%$ $Mn_{max} = 0.60\%$, ..., etc.	Non-Interview (Material Standards)

required at the beginning to determine the mechanical properties and chemistry information. KB I consists of information regarding the mechanical properties and chemistry corresponding to the material standards. The material standards include the Australian standards and other overseas standards transformed into a form which is similar to the Australian standards. Customer special standards are also included in KB I. Table 4.1 shows the three types of sample rules along with the KEL methodology utilised. C_{sac} refers to the value of carbon contents in the steelmaking aim chemistry. An example of the rules in KB I is shown below.

IF thickness is greater than or equal to 12
THEN *charpy test piece size is 10x10*

The rules regarding test piece size for charpy testing is based on the information in the material standards. Another example of the rules to be satisfied before matching of the tableaux rule base for charpy values (*char3678.tx)* is:

IF grade is AS3678-250-L15 or AS3678-300-L15 or AS3678-350-L15 or AS3678-400-L15
THEN *match tableaux "char3678.tx"*

Customer special requirements input through the interactive dialogue sessions are converted into the CSRCs through rules such as:

IF testing requirement is charpy AND
material type is structural steel AS3678 AND

value of minimum energy of longitudinal charpy testing is (average of three tests) less than or equal to 27 Joules and individual is less than or equal to 20 Joules. Test temperature is 0 °C or -15 °C

THEN *CSRC is 111*

Based on the Customer Special Requirement Codes (CSRCs), the chemistry and mechanical properties need to be modified. The knowledge rules required in accomplishing this are contained in the second knowledge-base KB II. Examples of rules in this include the rules for microstructure of the steel such as:

IF ASTM Grain size required is X

THEN Aluminium content should be Y

Another example of knowledge rules in KB II is shown below:

IF CSRC is 111
THEN *Maximum Sulphur is 0.020 and maximum hydrogen is 2.6 ppm.*

Input information regarding the end use of the steel or the intended application of the steel is an important factor in the material design. The end use along with information in KB I and KB II dictates a set of rules regarding elements to be included in the aim chemistry, range of values for each element in the aim chemistry and the basic process route to be followed. The basic process route could be hot rolled, control rolled, or normalised. These rules are included in the third knowledge-base KB III. Upper and lower values of aim chemistry determined by KB III are based on the assumption that a tolerance could be applied to the Certification Limits (CLIMs) values to obtain the

minimum and maximum values of aim chemistry. In case of carbon the minimum and the maximum values are given by :

$$C_{min} = \text{Lower value of CLIM} + 0.02 \text{ and} \tag{4.1}$$

$$C_{max} = \text{Upper value of CLIM} - 0.02 \tag{4.2}$$

Sample rules in the third knowledge-base (KB III) are shown below.

IF the steel type is structural steel
THEN *carbon in SAC is equal to minimum value of carbon in SAC*

IF grade is AS3678-250 OR AS3678-250-L15 OR AS3678-250Z
THEN *'red' is equal to 2*

Some values of aim chemistry, in spite of being within the range of values obtained through KB III, are not feasible due to practical difficulties faced by either the plate mill or the slab caster with the use of the above aim values. These limitations of aim values are represented in the fourth knowledge-base KB IV. This knowledge-base also contains values of the increments for all the elements in the aim chemistry, which are required while undertaking the iterative process. These increment values are based on the heuristic knowledge of the experts and range between 0.0001 and 0.01. Examples of increment values for carbon, niobium and boron are:

$$\Delta C = 0.005,\ \Delta Nb = 0.001, \text{ and } \Delta B = 0.0001$$

In the determination of the alloying elements and its contents the following two basic aspects are considered:

- Cost of alloying elements required to obtain 0.01 % increase in its composition.

- Increase in tensile strength and upper yield strength with the addition of 0.01% of the alloying element.

Based on the above criterion and the process limitations, rules are formulated which determine the optimum selection of alloying elements. Depending on the end use and the mechanical properties required, the strategy to be adopted in the determination of the aim chemistry is determined. These strategies could dictate whether high carbon low manganese steel is to be used or low carbon high manganese steel is preferable or other alloying elements are to be included. These rules are contained in KB IV. In the determination of aim chemistries, ratios between the values of some elements are to be always maintained. For example the ratio of copper to nickel should always be less than or equal to 2. All such restrictions of aim chemistries are also represented in the fourth knowledge-base KB IV.

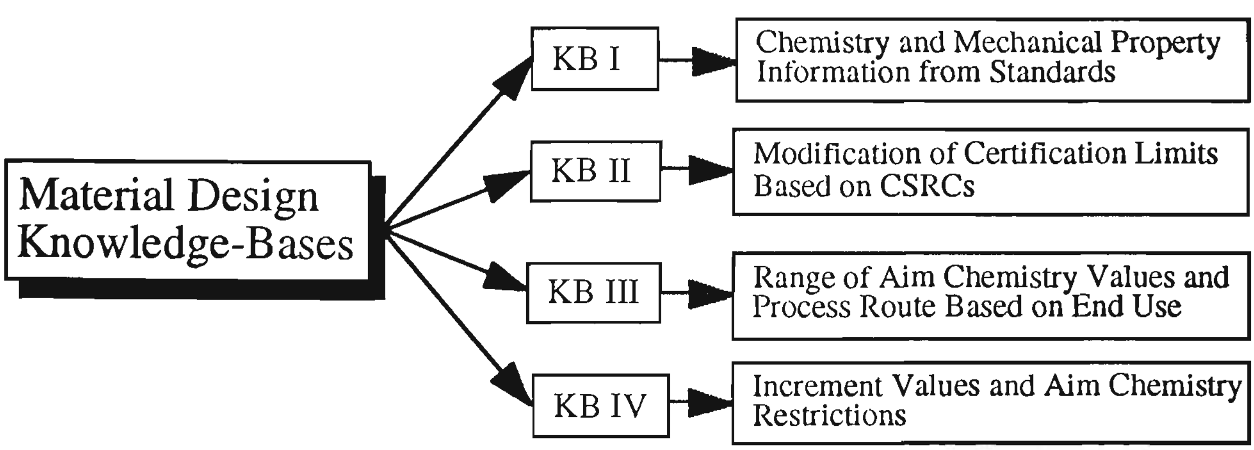


Figure 4.1 Knowledge-Bases for Material Design

Representative Examples of rules in KB IV regarding the chemistry restrictions which are utilised in the determination of steelmaking aim chemistries are shown below:

(Manganese in SAC)/(Carbon in SAC) >= 3

Avoid Carbon greater than 0.10 and less than 0.13 in SACs

Avoid Carbon greater than 0.18 and less than 0.20

The four knowledge-bases utilised in the prototype material design system are depicted in figure 4.1.

4.3 DETERMINING AIM CHEMISTRY

The hybrid methodology developed during this research utilises a knowledge base system approach along with mathematical modeling approach. The KBS approach is utilised to enable the use of the large knowledge bases, which are associated with the process of determining the SACs. The process of determining SACs also involves complex computations due to the iterative nature of the design process. Mathematical modeling developed during this research involves utilisation of various empirical models for determining the yield strength and tensile strength. It also utilises various carbon equivalent formulae in the iterative process. The iterative process in the mathematical modeling enables incrementing the values of various parameters and checking with the empirical models. This is undertaken to confirm that the SAC determined satisfies all the relevant empirical models along with the rules in the knowledge bases. The details of the iterative process are illustrated in the flow chart in figure 4.4.

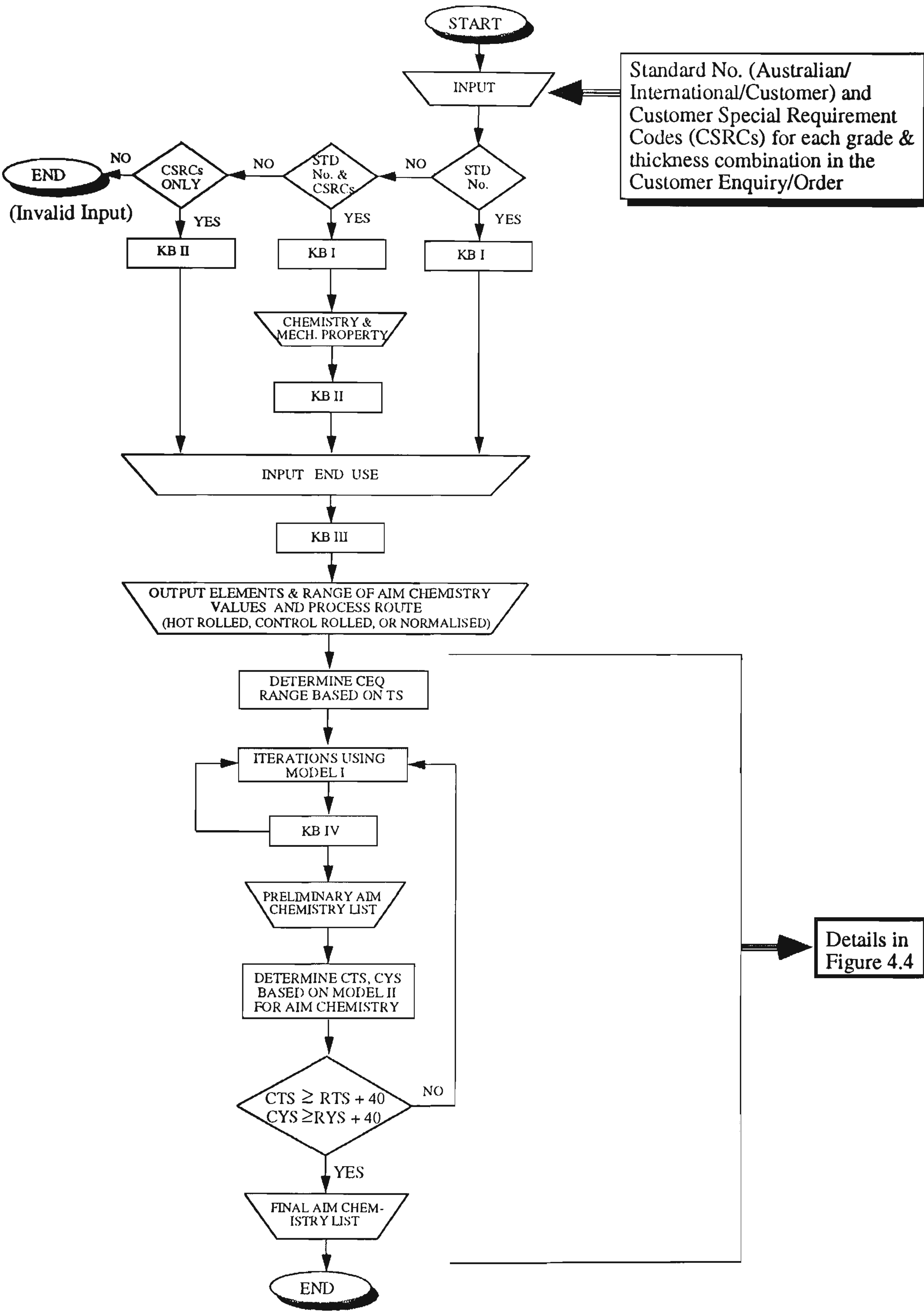


Figure 4.2 Basic Approach to Determine Steelmaking Aim Chemistry

Flow chart in figure 4.2 shows the approach adopted in the design of steelmaking aim chemistry. In this flow chart CEQ, CTS, CYS, RTS, RYS refers to carbon equivalent, computed tensile strength, computed yield strength, required tensile strength and required yield strength respectively. Model I depicts the empirical relationship between the carbon equivalents and the aim chemistry whereas model II depicts empirical relationship between tensile strength/yield strength and the aim chemistry. Input information from the user regarding the steel plate required is obtained through interactive sessions. The information about the material standard, its size, quantity, weight, end use and any customer special requirements is the input in the dialogue sessions as shown in figure 4.3. The customer special requirement codes are input through an interactive dialogue session. The system prompts if there is any customer special requirements. If Yes (Y) is prompted, a list of all the customer special requirements possible in the system such as charpy, RAZ, etc. is displayed and the user has to choose one from this list. Based on this input (major code) another screen is displayed which has all the types of steels considered in the system. Finally, based on this choice of the type of steel (sub group code), the corresponding value codes are displayed and the user is prompted to choose one value (value code). These three inputs are then converted into CSRCs such as 211, 112, etc. by the system. Depending on the type of inputs the knowledge-base KB I is accessed and the details about the chemistry and mechanical properties are retrieved mainly based on the information from the material standards. This information from the standards is modified to take into account the customer special requirements based on KB II. The CLIMs are thus obtained. By utilising this CLIM and KB III, the elements that are to be considered in the aim chemistry are determined. The basic process route is also determined based on the knowledge rules in KB III.

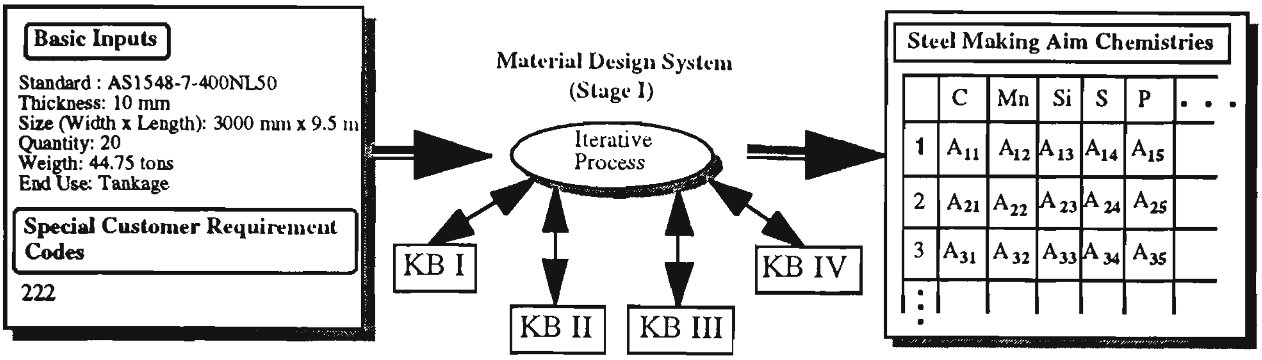


Figure 4.3 System Input/Output

Based on CLIM, initial values of the aim chemistry for iteration can be obtained by applying KB III. The upper and lower values for all the elements in the aim chemistry are determined through KB III. The next stage is the iterative process along with the application of the expert and heuristic knowledge. This process is illustrated in detail in the iterative flow chart of figure 4.4.

Empirical relationship between the CEQ and the mechanical properties are utilised to determine the range of CEQ values that are required to achieve the desired mechanical properties. The CEQ range values are obtained by analysing the database having performance data corresponding to steel grade and thickness combinations. The steel grade and thickness combination nearest to the one required is considered in the determination of the CEQ range. A representative graph of CEQ versus tensile strength, based on the above database is illustrated in figure 4.5.

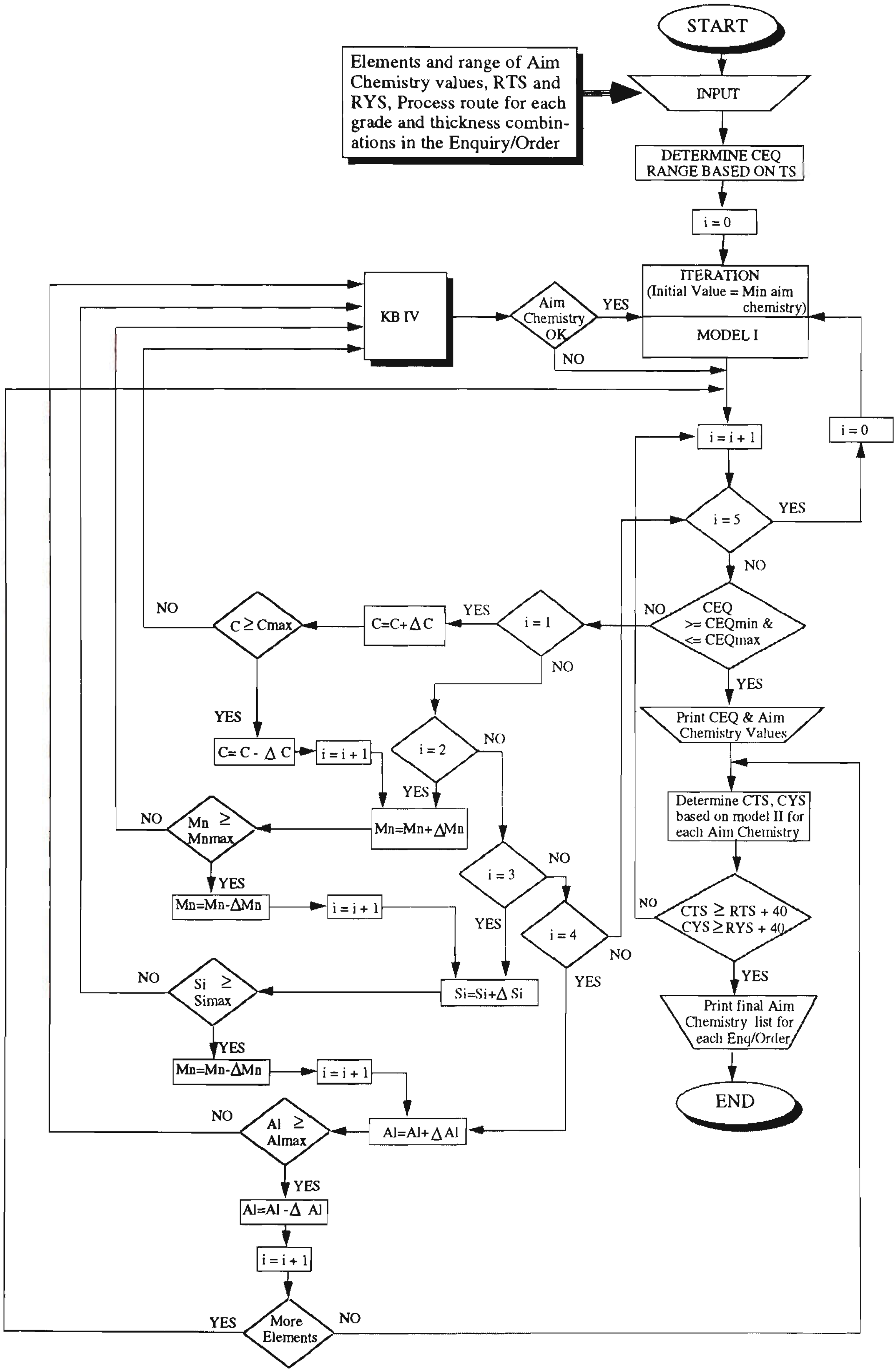


Figure 4.4 Flow Chart for Iterative Process
(This is Part of Figure 4.2)

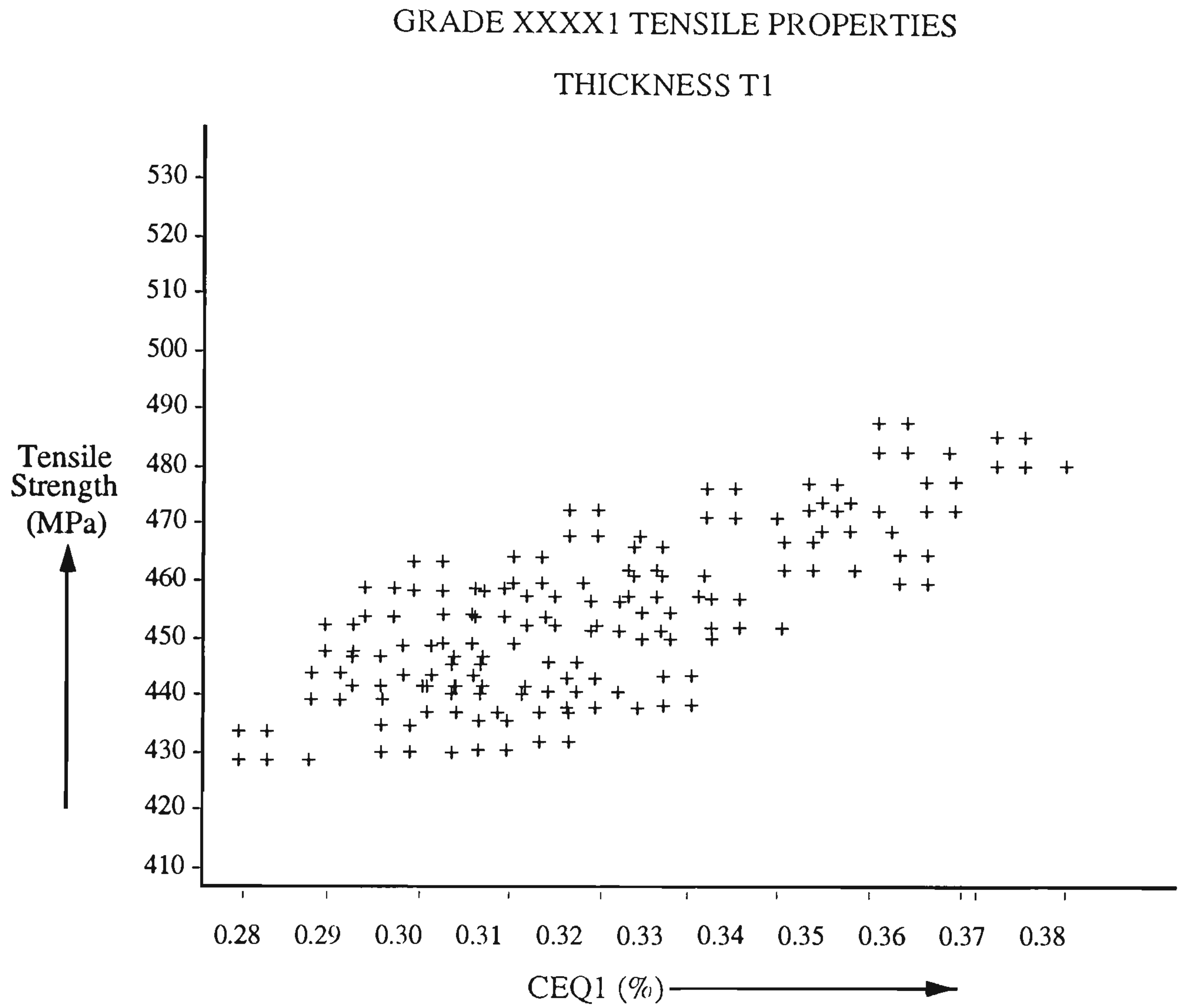


Figure 4.5 Representative Graph of CEQ vs Tensile Strength

The range of values that the aim chemistry can take, the elements to be considered in the aim chemistry, the basic process route and the CEQ range computed above are all used as inputs in the next stage of iterative process explained below. The relationship between various carbon equivalents and the aim chemistry generally used at BHP Steel, Port Kembla, is expressed by the following equations:

$$CEQ1 = C + \left(\frac{Mn + 10P + Si}{6}\right) \tag{4.3}$$

$$CEQ3 = C + \left(\frac{Mn}{6}\right) + \left(\frac{Cr + Mo + V}{5}\right) + \left(\frac{Ni + Cu}{15}\right) \tag{4.4}$$

Different material standards specify different formulae for the computation of the carbon equivalents. Equation 4.3 gives a carbon equivalent sometimes used internally by BHP Steel. The carbon equivalent given in equation 4.4 is developed by International Institute of Welding (IIW) and is the general formula used by most material standards.

$$R1 = Ni + Cr + Cu \tag{4.5}$$

$$R2 = Cu + Ni + Cr + Mo \tag{4.6}$$

The governing chemical requirements given by equations 4.5 and 4.6 are also used internally by BHP Steel to check whether the aim chemistry satisfies these equations. These represent some restrictions on the aim chemistry. Depending on the requirements from the standards and the end use, one or more of the above equations are utilised in the iterative process. Initial values for the iterative process are the lower values of the aim chemistry determined by applying the tolerances given in equations 4.1 and 4.2. The minimum chemistry is first tried and checked to see whether this chemistry is enough to get the CEQ value within the range obtained by using figure 4.5. If this chemistry is not enough to achieve the CEQ then the value of carbon is incremented in step of ΔC based on the heuristic knowledge of the experts (KB IV). Again the iterative process is continued as illustrated in the flow chart of figure 4.4, by incrementing the values of other elements within the range of aim chemistry values determined earlier. As the values of aim chemistry elements are scanned in KB IV before iterations begin, the situation where the aim chemistry becomes richer in one

element and leaner in some other element is also avoided. For example, after incrementing the value of carbon, it is scanned to see if the ratio of carbon to manganese is within the range specified in KB IV. If it is not, this value of carbon is discarded and manganese is incremented as shown in the flow chart in figure 4.4 and the iterations continue. For the purpose of simplicity, only four elements are considered in the iterative process shown in figure 4.4. In the actual system all the elements (15) are included in the iterative process.

The knowledge-base (KB IV) is applied after each increment to check whether the value of aim chemistry obtained is feasible. A list of preliminary aim chemistry values are thus obtained by the application of the iterative process along with the knowledge-base application. Thus it is very important to apply the knowledge-base to check each value of the aim chemistry before commencing the iterations.

The aim chemistry values thus obtained are further checked to confirm that they are sufficient to obtain the required Tensile Strength (TS) and Upper Yield Strength (UYS). Relationships between the chemistry, mechanical property, reduction ratios, and the final rolling temperatures developed at BHP Steel, Port Kembla, are depicted below [28]:

$$\begin{aligned} UYS = F_1 - F_2\,FRT + F_3C + F_4Mn + F_5Si + F_6Cu + F_7Nb + \\ F_8P + F_9Red - F_{10}Thk \end{aligned} \tag{4.7}$$

$$\begin{aligned} TS = T_1 - T_2\,FRT + T_3C + T_4Mn + T_5Si + T_6Ti - T_7Cu \\ + T_8Ni + T_9Nb - T_{10}P + T_{11}Red - T_{12}Thk \end{aligned} \tag{4.8}$$

$F_1, F_2, ... F_{10}$ and $T_1, T_2, ... T_{12}$ in the above equations are constants which depend on the interrelationships between various process parameters and the aim chemistry, *FRT*

is the final rolling temperature, *Red* is the reduction ratio and *Thk* is the thickness of steel plates.

The empirical models derived from the statistical data are utilised for this process. As these empirical models are characterised by an error of about ±20 MPa in the prediction of tensile strength and upper yield strength, a safety factor of 40 MPa is added to the required values of tensile strength and upper yield strength while comparing with the computed values of tensile strength and upper yield strength. Thus the final aim chemistry list is generated which consists of alternative aim chemistries that satisfy any customer requirements.

Figure 4.3 also shows dummy output of steelmaking aim chemistries generated by the system. A_{ij}'s represent dummy steelmaking aim chemistry values generated by the prototype system described in this chapter. Here i represents the number of sets of steelmaking aim chemistry values. The prototype system generates about 15 to 30 sets of values of the contents of various elements for each combination of grade and thickness required by the customer. In actual practice 15 elements are considered in the system and hence each set of aim chemistry values consists of 15 individual values of contents of various elements and the maximum value of j is 15. Each of the aim chemistry values A_{ij}'s (i lies between 15 to 30 and j = 1, 2, ... 15) has to satisfy a number of criteria such as the empirical models (equations such as equations 4.3 to 4.8), material standards and the knowledge rules including expert and heuristic knowledge rules. The basic information about the material given by the customer, along with the information from the corresponding material standards, dictates a broad range of aim chemistry values. This range is further refined to take into account the customer special requirements. This is done by firing of appropriate knowledge rules

contained in KB II corresponding to the CSRCs. Each of the values of A_{ij}'s is checked to see that it does not violate any of the limitations or constraints of the production units. If an attempt is made to obtain these aim chemistry values based on manual computations, it would be too time consuming due to the enormous computations involved and more importantly may require the knowledge rules from a number of experts. Due to these reasons the system is expected to perform better than the experts.

4.4 SUMMARY AND CONCLUDING REMARKS

Due to the interaction of many complex factors in material design it is very difficult to systematise the process by the application of mathematical approach alone. It is attempted in this chapter to eliminate the problems faced in this direction. The application of the knowledge rules containing expert's process knowledge, metallurgical knowledge and also the heuristic knowledge can be to a great extent useful in determining the steelmaking aim values that are practically feasible for the slab caster and the plate mill. The quality of the output of this system depends mainly on the quality of the rules in the knowledge-bases. The knowledge-base grows richer by experience and it is always possible to incorporate more rules in the knowledge-bases by learning from the experiences and the mistakes in the past. This system is expected to assist the metallurgists in the design of new steel material by taking up the cumbersome task of iterations and by utilising the expert knowledge and heuristic knowledge from a group of experts.

The aim chemistry list for each customer requirement thus obtained by the application of the mathematical and knowledge-based approach is the output of first stage of the prototype material design system developed at BHP Steel, Australia. The next stage

involves the application of fuzzy logic to rank the aim chemistries by utilising the grade history database containing statistical data.

CHAPTER 5

CHAPTER FIVE

RANKING OF STEELMAKING AIM CHEMISTRIES UTILISING FUZZY MEMBERSHIP FUNCTIONS

5.1 INTRODUCTION

The system described in the previous chapter designs steelmaking aim chemistries. Steelmaking aim chemistry here refers to the composition of the molten steel produced at the basic oxygen steel making furnace, which has been processed to make it suitable for the continuous casting machine. This system generates about 15-30 different steelmaking aim chemistries for each combination of grade and thickness corresponding to the customer orders. Having several alternatives is desirable to facilitate optimisation by trading off some parameters at the expense of others. All these alternatives could be used to produce the customer order, but with different desirability factors. Fuzzy logic is applied in the material design system as depicted in figure 5.1, to rank the alternative steelmaking aim chemistries according to the degree which will satisfy the customer's requirements of chemistry and mechanical properties, with due consideration given to the economic aspects and the complexity involved in the production. Four factors considered in the development of the membership functions include chemistry, mechanical properties, relative cost and the complexity involved in the production of the steel material.

Design of membership functions is an important task in the development of fuzzy logic based systems. Membership functions could be obtained by using statistical information combined with processes developed to compute it. The development of individual, composite and Weighted Sum Membership Functions (WSMFs) which is very important in realistically ranking the steelmaking aim chemistries is discussed in this chapter. The complexity factor not considered by other researchers has been included as an important component in the development of the WSMF. A methodology has been developed to obtain membership function corresponding to this complexity factor. This chapter also describes the development of a set of equations required to compute the WSMF for the relative cost factor.

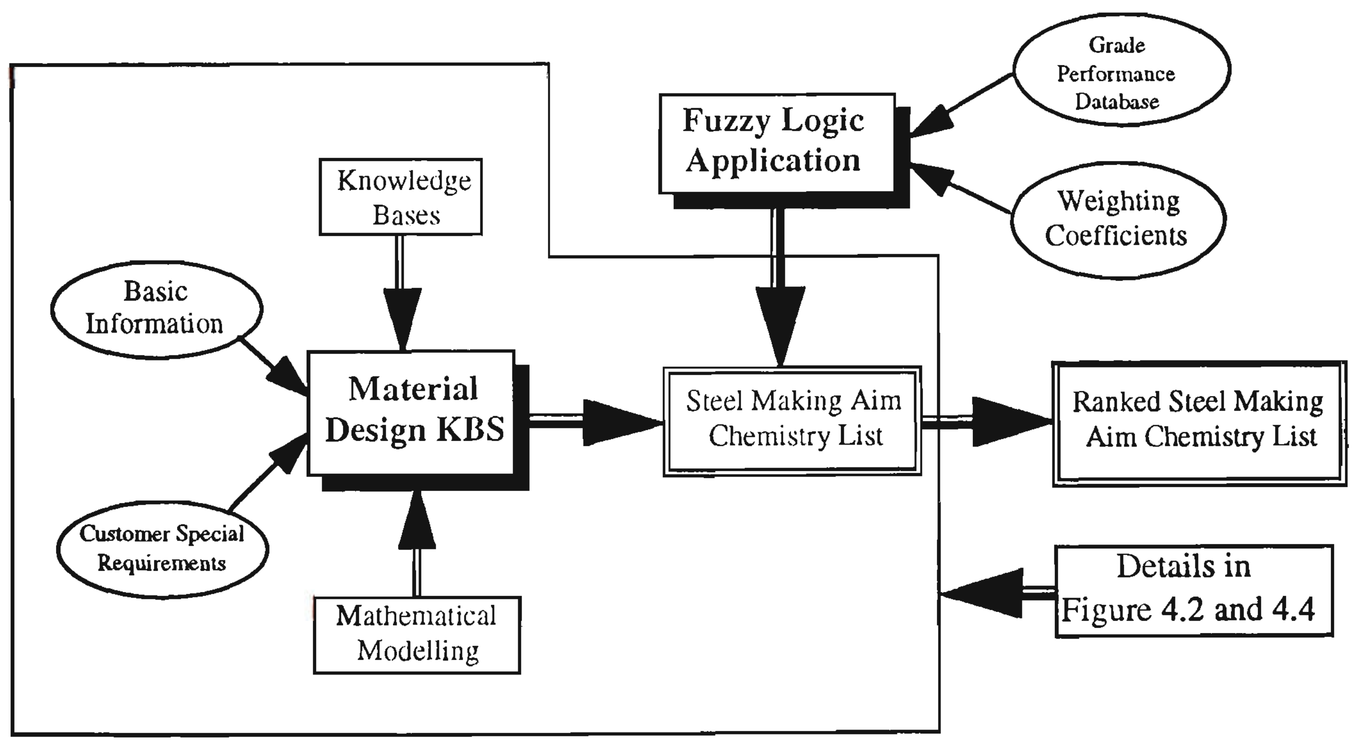


Figure 5.1 Application of Fuzzy Logic

5.2 RANKING OF STEELMAKING AIM CHEMISTRIES

The performance of a steelmaking aim chemistry based on the chemistry and mechanical property, could be described statistically by a Probability Density Function (PDF). For example the tensile strength achieved by a given steelmaking aim chemistry can be approximated by a normal distribution. Membership functions for chemistry and mechanical property could be defined to measure how closely the steelmaking aim chemistry satisfies the customer requirements based on the performance data in the grade history database for the grades produced in the past.

5.2.1 Development of Fuzzy Membership Function Utilising Probability Theory

Development of fuzzy membership functions to measure how closely the steelmaking aim chemistry satisfies the customer requirements of chemistry and mechanical property, could be achieved by the application of probability theory. The database of performance of the grades made in the past is utilised for this purpose. Uncertainty encountered in this process of measuring the ability of the grades to meet customer requirements is probabilistic in nature. Fuzzy set theory in conjunction with probability theory could be successfully applied to model the uncertainty and imprecision inherent in such situations as explained below.

The data regarding chemistry and mechanical property in the grade history database could be assumed to be normally distributed and could be approximated by a PDF. With this assumption a methodology could be developed to measure the ability to meet customer requirements.

The PDF for a normal distribution is given by the equation [81]:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} , \qquad -\infty < x \infty \tag{5.1}$$

where μ = mean and σ = standard deviation.

The Cumulative Density Function (CDF) of the normal distribution is given by the equation

$$F(x) \;=\; \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(y-\mu)^2/2\sigma^2} dy \tag{5.2}$$

Typical curves for the PDF and CDF of the normal distribution are shown in figure 5.2 below:

Normal tables are utilised in the computation of $F(x)$, as equation (5.2) cannot be solved readily. Normal tables give the value of $F(x)$ in terms of the variable x.

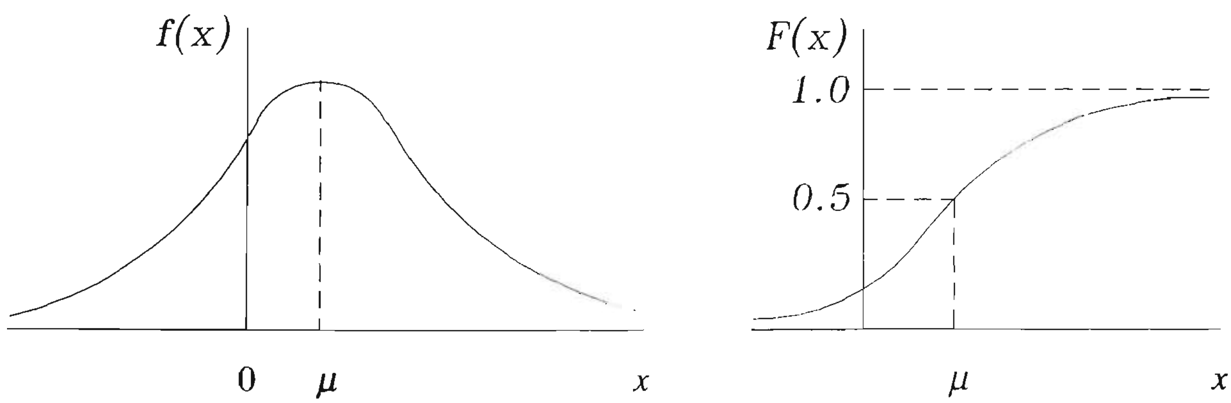


Figure 5.2 PDF and CDF curves for Normal Distribution [81]

The standardised normal value z defined by the equation

$$z = (x - \mu) / \sigma \tag{5.3}$$

is used to determine the area under the normal curve for various values of z. By substituting equation 5.3 into equation 5.1 the standard normal PDF could be obtained and is given by

$$\phi(z) = e^{-z^2/2} / \sqrt{(2\pi)}, \quad -\infty < z < \infty \tag{5.4}$$

For $\mu = 0$ and $\sigma = 1$, the corresponding CDF is given by

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy \tag{5.5}$$

The normal tables are based on these equations and are utilised in the computation of the membership functions. A copy of the normal tables [67] is included in Appendix C. This is utilised in one of the programs coded in C language to compute the fuzzy membership functions indicating the degree to which steelmaking aim chemistry meets customer requirements of chemistry and mechanical property. Customer requirements of chemistry and mechanical property along with the mean and standard deviation (of the grades nearest to the one required by the customer) values in the grade history database enables these computations.

5.2.2 Membership Function Components

The components of fuzzy membership functions considered by other researchers [91-92], [97-98] to rank alternative steel grades include mechanical properties, chemistry and desirability. If the ranking is done by utilising the above three components it would not be realistic due to the fact that the dynamic component which depends on the current plant situation and the relative importance of the orders is not considered. The desirability component above is a penalty function for deviating from the minimum cost and/or easiest to produce grades. The work done in references [91-92], [97-98] does not consider the variable component which depends on the current plant situation and the relative importance of the orders. Due to these the ranking accomplished may not represent the realistic situation. To overcome this it is proposed to use the following components in the development of the membership functions:

- Mechanical Properties
- Chemistry
- Relative Cost and
- Complexity

Introduction of the last two factors in place of the desirability component used by the previous researchers enables ranking of the steel grades in a realistic manner reflecting all the limitations/restrictions encountered at various production units. Each of the above components are described below.

5.2.2.1 Mechanical Property Component

Assume that there are K different mechanical properties, such as tensile strength, yield strength, etc., which are important for a customer order. Let $\overline{X}(j,K)$ and $\sigma(j,K)$ be the mean and standard deviation, respectively, that grade G_j achieves with respect to mechanical property K where $K = 1, 2, ..., U$. In other words, when grade G_j is produced, mechanical property K has a value $X(j, K)$ which is assumed to be approximately normally distributed. Furthermore, for each customer order S_i, let $m(i,K)$ and $M(i,K)$ be the minimum and maximum specified levels for mechanical property K. Combining these values, the membership function can be defined as

$$\begin{aligned} &f_{A(i,K)}(G_j)=\text{Prob}\,[m(i,K)\leq X(j,K)\leq M(i,K)] \\ &\text{for } j=1, 2,\dots,N; \quad i=1,2,\dots,M; \text{ and } K=1,2,\dots,U \end{aligned} \tag{5.6}$$

Here j = 1, 2, ..., N represents the number of grades and i = 1, 2, ..., M represents the customer orders. $f_{A(i,K)}$ is defined to measure how well a grade satisfies customer C_i's requirement for mechanical property K and has a range of [0, 1].

5.2.2.2 Chemistry Component

In a similar way assume that there are L different chemical elements such as carbon, manganese, etc., which are important for a customer order and $L = 1, 2, ..., V$. Let $\overline{X}(j,L)$ and $\sigma(j,L)$ be the mean and standard deviation, respectively, achieved by grade G_j with respect to chemical element L. Also, for each customer order S_i, let $m(i,L)$ and $M(i,L)$ be the minimum and maximum specified levels for chemical element L in order S_i. Therefore, the membership function can be defined as

$$f_{A(i,L)}(G_j) = \text{Prob}\,[m(i,L) \le X(j,L) \le M(i,L)]$$
$$\text{for } j=1, 2, \ldots, N; \quad i=1,2,\ldots,M; \text{ and } L=1,2,\ldots,V \tag{5.7}$$

5.2.2.3 Relative Cost Component

Let $f_P(G_j)$ be the membership function of the fuzzy subset of G based on the relative cost of producing the grade G_j. This relative cost component includes the cost of the alloying elements added to grade G_j and the cost of various processes involved in the production of the grade, as depicted in equation below.

$$f_P(G_j) = \sum_{i=1}^{15} A_i E_i + \sum_{k=1}^{9} B_k \tag{5.8}$$

Here A_i's represent the coefficients required in the computation of the alloying cost component of the relative cost factor. Representative values of A_i's include A_1 corresponding to the element carbon, A_2, corresponding to the element manganese, etc. E_i's represent the contents of various elements in the steelmaking aim chemistries. Representative values of E_i's include E_1 which is the content of element carbon, E_2 which is the content of element manganese, etc. As 15 elements are considered in the process of determining the steelmaking aim chemistries, the values of i varies between 1 and 15. First term in the above equation ($\sum_{i=1}^{15} A_i E_i$) is the alloying cost component. The minimum and maximum values of this component are 0 and 0.60 respectively as 60 % weightage has been given to this in the relative costing process. Similarly the second term ($\sum_{k=1}^{9} B_k$) which represents processing cost component has minimum and maximum values of 0 and 0.40 respectively as 40 % weightage has been given to this component. These relative weightages have been given based on the results of the KEL process,

which is mainly due to the intuition of the experts. B_k's indicate the requirement of special processing. Some representative values of B_k's are shown below:

$B_1 = 0.05$ if Hot Stacking is required; otherwise $B_1 = 0$

$B_2 = 0.05$ if Normalising is required; otherwise $B_2 = 0$

As nine factors have been identified which affect the processing at various production units, therefore the value of k ranges between 1 and 9. Cost of storage also adds to the cost of steel product. This cost depends mainly on the size of steel plates and its tonnage. However, this additional cost is common to all the steel products rolled and hence is not considered in the relative costing process.

The cost of a grade increases with a decrease in the composition of carbon, therefore the value of coefficient A_1 decreases with decrease in the value of carbon contents. In contrast, the values of other coefficients (A_2, A_3, .., A_{15}) increases with a decrease in the value of the contents of the corresponding elements. Thus the cost of adding the alloying elements could be simply obtained based on the amount of various elements present in the grade G_j. The values of the coefficients are determined based on the minimum and maximum values of the contents of the elements and the impact of these contents on the cost of the grade. The following examples would clarify this further.

The minimum and maximum values of the carbon contents normally used in steelmaking are 0.05% and 0.20% respectively. The corresponding values of the product of carbon content and the coefficient A_1 for this range of carbon contents are 0 and 0.04 respectively. This range of values is based on the weighting given to carbon contents in the relative costing process which means that 4% of weighting is given to carbon

contents in determining the relative cost component. The variation of the carbon contents and the product of carbon contents and the coefficient A_1 is linear. Hence if a simple curve is fitted as shown in figure 5.3 utilising the above data, the value of the coefficient could be obtained by the equation (Symbol '*' denotes the multiplication sign.)

$$A_1 = (-0.013333 + 0.26667 * C) / C \tag{5.9}$$

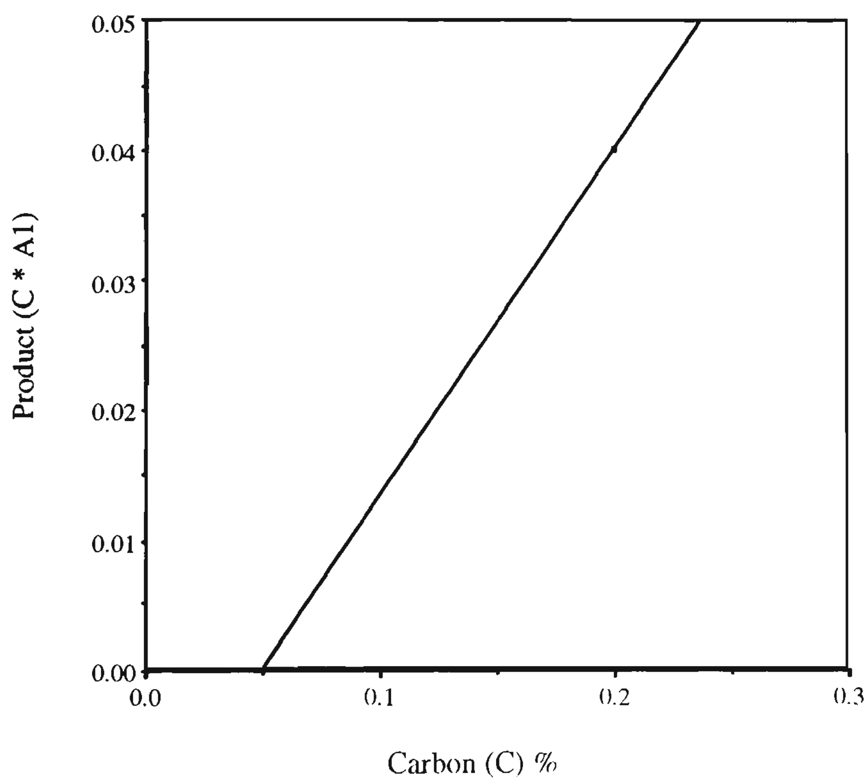


Figure 5.3 Relationship between C and C * A_1

Table 5.1 Data to compute A_1, A_2 and A_3

	Carbon	Manganese	Silicon
Min Value of Element	0.05%	0.20%	0.01%
Max Value of Element	0.20%	2.0%	0.50%
Value of coefficient	A_1 = (-0.013333 + 0.26667 * C) / C	A_2= (-0.0044444 + 0.022222*Mn) / Mn	A_3 = (-0.000081633 + 0.081633 * Si) / Si

The values of the coefficients A_2 and A_3 for manganese and silicon contents are obtained based on the above methodology, utilising the values given in table 5.1 and the graphs in figures 5.4 and 5.5 respectively.

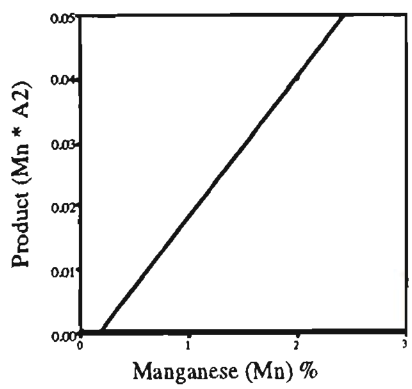


Figure 5.4 Relationship between Mn and (Mn * A_2)

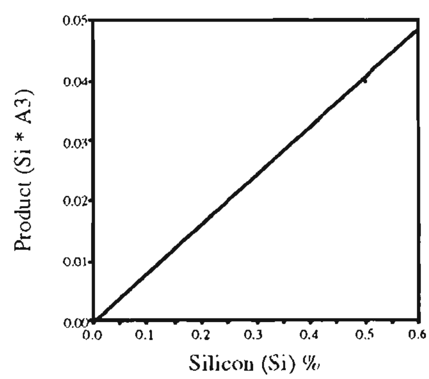


Figure 5.5 Relationship between Si and (Si * A_3)

Utilising this methodology the values of all the coefficients A_i's could be determined based on the values of the elements in the steelmaking aim chemistry, their maximum and minimum permissible values and the relative weightages in the relative costing process.

Relative cost component is normalised to have a range of [0, 1], 1 representing the most cost effective grade. This factor is independent of any particular customer order.

5.2.2.4 Complexity Component

Let Q be a fuzzy subset of G and $f_{Q(i)}(G_j)$ be the corresponding membership function based the complexity involved in the production of the grade G_j. The value of $f_{Q(i)}(G_j)$ is normalised to have a range of [0, 1], where 1 represents a membership value which is characterised by a grade with maximum ease of production. The three components described above are of fixed type and do not depend on other factors. Complexity component is a variable factor and depends on the plant situation at any instant of time and the relative importance of the customer orders. During KEL process it became apparent that in the fuzzy ranking technique it is very important to include a complexity factor to achieve realistic ranking of the steelmaking aim chemistries. Realistic ranking of SACs is not feasible unless a dynamic factor which depends on the current plant situation and the importance of the customer orders is considered. Complexity component in the fuzzy ranking process is developed to consider such plant restrictions or limitations which are dynamic in nature. The variables affecting this factors include:

- Hot stacking capacity
- Normalising capacity
- Vacuum degassing capacity
- CaSi injection capacity
- Control rolling capacity
- Al alignment at caster
- Nature of the order

- Scarfing capacity
- Air cooling capacity

Customer orders could not be rolled due to the presence of one or more of the above variables at a particular instant of time. The capacity available at various processing units at any instant of time is hence very important in deciding the most desirable alternative steelmaking aim chemistry. For example there are situations when there is no space available to hot stack the steel plates rolled as all the space has already been occupied by previous orders. In such cases even though the grade satisfies chemistry, mechanical properties and relative cost factors, it could not be produced during that time due to the unavailability of space for hot stacking. In this case the value of $f_{Q(i)}(G_j)$ is taken as zero because of the fact that it is not feasible to produce this grade due to the complexity factor. Similarly A1 alignment at the caster is not possible at some stage in the maintenance cycle of the caster. Therefore if an order requires A1 alignment at this instant of time, the particular order could not be cast due to this restriction.

Nature of the order is another important factor in the ranking process. For example an order for a small quantity of complex grade and a large quantity of relatively simple grade might be accepted. This is because of the fact that, the large quantity might not be ordered if the small quantity is not accepted. Another reason for the acceptance of such orders may be strategic in nature.

The complexity component could be determined mainly by answering a set of queries based on the above factors. This could be achieved through an interactive dialogue session. Responses to the queries such as - "Capacity available for hot stacking?", could

be selected from a list of choices. Responses to all the relevant queries from the choices presented could be utilised to determine the value of the complexity factor.

5.2.3 Composite Membership Component

As the chemistry and mechanical property requirements are of equal importance, the limiting case is always the chemistry and mechanical property element with the lowest probability. The minimum value of the membership functions of the chemistry component and the mechanical properties component are critical in determining how closely the grade G_j satisfies the mechanical properties and chemistry corresponding to the customer order i. For this reason the composite membership functions for mechanical properties and chemistry could be obtained by

$$\begin{aligned} f_{K(i)}(G_j) &= \min_K \{ f_{A(i,K)}(G_j) \} \\ f_{L(i)}(G_j) &= \min_L \{ f_{A(i,L)}(G_j) \} \end{aligned} \tag{5.10}$$

which are based on the formula proposed by Zadeh [103]. This process of determining composite membership by applying the "min" operator is illustrated in figure 5.6.

5.2.4 Weighted Sum Membership Function

Having determined the composite membership functions for the mechanical properties and chemistry components, the WSMF for the fuzzy subset $A(i)$ of G could now be determined. This WSMF measures the ability of a grade to meet all the chemistry and mechanical property requirements of customer order S_i, taking into consideration the relative cost and the complexity involved in the production of the grade. Let $G_j \in G$,

then based on Bellman and Zadeh [5], the WSMF for grade G_j corresponding to customer order i is given by

$$f_{A(i)}\left(G_j\right)=\begin{cases}\beta_1 f_{K(i)}+\beta_2 f_{L(i)}\left(G_j\right)+\beta_3 f_P\left(G_j\right)+\beta_4 f_{Q_{(i)}}\left(G_j\right) \\ \qquad \text{if } \min\left\{f_{K(i)}\left(G_j\right), f_{L(i)}\left(G_j\right)\right\}\neq 0 \text{ or } f_{Q(i)}\left(G_j\right)\neq 0 \\ 0 \quad \text{if } \min\left\{f_{K(i)}\left(G_j\right), f_{L(i)}\left(G_j\right)\right\}=0 \text{ or } f_{Q(i)}\left(G_j\right)=0\end{cases} \tag{5.11}$$

where $\beta_1+\beta_2+\beta_3+\beta_4=1$ and $\beta_1>\beta_2>\beta_3>\beta_4$

βs in this equation are the weighting coefficients. All the four components of the WSMF are not of equal importance and hence the weighting coefficients have different values depending on the relative importance of the four factors. βs are determined mainly based on metallurgical and economic considerations. Selecting proper values of βs is very important in ranking of the aim chemistries. Typical values of βs include β_1= 0.40, β_2= 0.30, β_3= 0.18 and β_4= 0.12. These values are based on the relative importance given by the experts to the four components in the ranking process. The values of βs are mainly based on metallurgical and production constraints. Using a different set of values of βs reflecting the relative weightages of the four components, results in change in the priorities of the steelmaking aim chemistries. Experts utilise their intuitive judgement in determining these values. Development of WSMF based on the four components is depicted in figure 5.6.

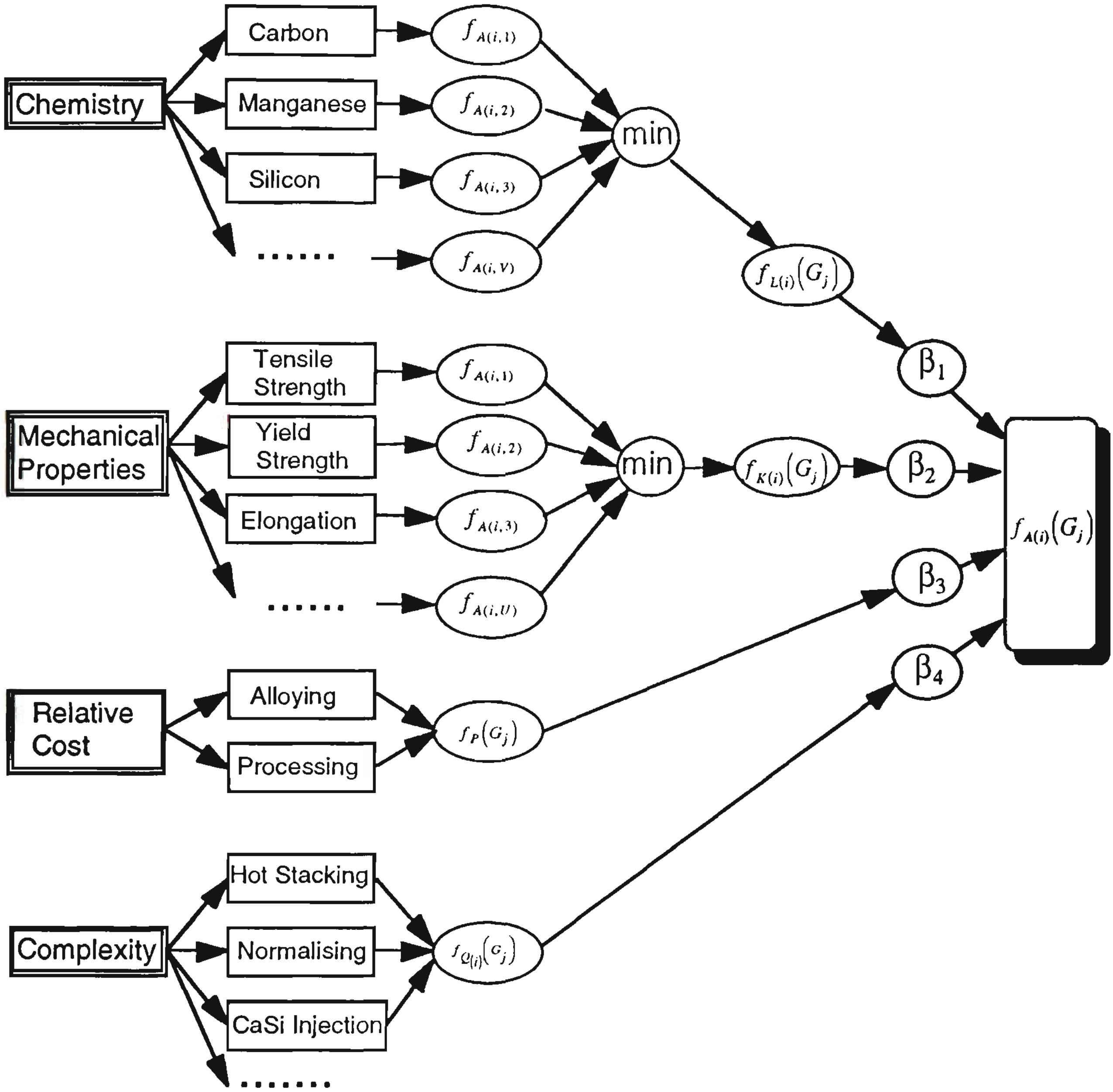


Figure 5.6 Components of Weighted Sum Membership Function

5.3 RESULTS AND ANALYSIS

The software module developed based on the methodology described in this chapter ranks the steelmaking aim chemistries generated by the software module developed based on the methodology described in the previous chapter. The ranking is

accomplished by first reading each of the steelmaking aim chemistries. It then computes the individual, composite and the weighted sum membership function for each of the four components viz. chemistry, mechanical property, relative cost and complexity. The weighting coefficients (β_1, β_2, β_3 and β_4)are utilised in the computation which depend on the relative importance of each of the four components.

Individual membership functions for chemistry components are computed based on equations 5.3 and 5.6 along with mean and standard deviation data from the grade history database. Applying the "min" operator, the composite membership function is determined, which is the minimum value of the individual membership functions for the chemistry components. The same process is applied to determine the individual membership functions and the composite membership function for the mechanical property components.

Relative cost membership function is computed based on equations 5.8 and 5.9 along with data such as shown in table 5.1. Determination of the complexity component is quite straight forward and depends on the existence of the factors affecting this membership function.

The weighted sum membership function for the steelmaking aim chemistries corresponding to the combination of grade AS3678-250 and thickness 10 mm are illustrated in Appendix E. Computation of the WSMF in this case is based on the following values of βs: $\beta_1 = 0.40$, $\beta_2 = 0.30$, $\beta_3 = 0.18$ and $\beta_4 = 0.12$. The steelmaking aim chemistries are sorted in the decreasing order of the weighted sum membership functions as shown. Higher values of the weighted sum membership function indicates a steelmaking aim chemistry which is more desirable. Ideally, the steelmaking aim

chemistry with the highest weighted sum membership function should be the one which is used to produce the grade and thickness combination under consideration. In other words, the steelmaking aim chemistry with the highest value of weighted sum membership function should be the recommended steelmaking aim chemistry for the grade and thickness combination under consideration. This is not the case in the ranked steelmaking aim chemistry list shown in Appendix E. This could be due to the fact that the relative importance of the four components reflected in the weighting coefficients may not be the appropriate values. Further knowledge elicitation is required in this area to obtain realistic values of the weighting coefficients. Determination of the relative cost membership function also needs further refinement to obtain membership function values which realistically project the actual relative cost of various alternative steelmaking aim chemistries. Further research is required to determine the actual impact of the contents of various elements in the steelmaking aim chemistry on the cost of the grade and also to determine the appropriate weightages of the alloying cost and process cost components in the relative costing process.

Determination of the complexity membership function similarly needs further research to refine the computation to get realistic membership function values. This again could be achieved by further knowledge elicitation to determine the relative impact of the nine factors identified earlier. Interaction of the various factors affecting the complexity component requires further study to determine actual impact on the membership function value. The nine factors which affect the complexity membership function, may not be the only factors affecting this membership function. Further research is required to identify the existence of other factors affecting the complexity membership function.

5.4 SUMMARY AND CONCLUDING REMARKS

Fuzzy Logic has been successfully applied to rank the alternative steelmaking aim chemistries based on the four variables viz. chemistry, mechanical properties, relative cost and the complexity involved in the production of steel plates. This methodology takes into consideration the dynamic aspects effecting the production of steel through the complexity factor, which makes the ranking more realistic. The set of simple equations developed to compute the relative cost membership function enable the determination of this membership function with ease.

This methodology could also be successfully applied to other areas by considering appropriate factors corresponding to the problem at hand. This methodology has practical significance as there are several cases where the solution is not unique and there are several alternatives and the objective is to rank the alternatives in a order of desirability by considering various factors. This is usually the case in the design field.

CHAPTER 6

CHAPTER 6

CODIFICATION AIDED GRAPHICAL USER INTERFACE FOR MATERIAL DESIGN SYSTEM

6.1 INTRODUCTION

User interface is the presentation of the underlying program that allows one to accomplish his/her communication task - how the program looks on the computer screen and how it handles input and output [50]. Graphic User Interface (GUI) is usually preferred to Text-based User Interface (TUI) as the former gives the user options through icons placed on the desktop. In GUI, a user can navigate across a desktop using a mouse to click on graphical icons, directing the hardware and software to perform commands. In addition, the user has access to pull down menus. In the TUI, the user is required to know what to ask, and to type commands at a prompt, instead of just clicking on an icon.

One of the reasons for the failure of knowledge-based systems is that the developers often do not always give the required attention on the user interface which is a most crucial part of the system. Great efforts are required in conceptual design, formal specification and implementation of user interfaces to achieve a high level of user acceptance. User interface development occupies a large part of an application development time. About 48% to a maximum of nearly 100% of the code for an interactive system is used to support the user interface [56]. Thus user interface becomes

a crucial part of the whole interactive system and user interface development is becoming an integral part of the overall software engineering process. Different factors that are to be considered in the design of a user interface have been described in reference [94], which include simplicity, reliability to prompt reaction, minimum operator key strokes, etc.

The importance of "useability" in the development of user interfaces has been well described by Hix and Hartson [30]. According to the authors useability is a combination of the following user-oriented characteristics:

- Ease of learning
- High speed of user task performance
- Low user error rate
- Subjective user satisfaction
- User retention over time

That is, useability is related to the effectiveness and efficiency of the user interface and the user's reactions to that interface. The naturalness of the interface for the user is also an important aspect of useability.

Application of artificial intelligence techniques to develop an intelligent interface has been described by Myers and Rosson [56]. The interface developed is called Decisional Module of Imagery (DMI). The approach consists of using an expert system to manipulate the three objects: “What”, “When” and “How” in the field of complex process control. This interface provides a means of controlling screen displays by

providing advice to the controller of a complex process about the current status of the process and the control action suggested.

The design and specification of a user interface which is oriented towards the need of end users and which is based on sound conceptual and formal framework is described by Stary and Pasztor [78]. This research is focussed on the development of a comprehensive specification technique, comprising static as well as dynamic aspects of end user tasks and their decomposition into structures and procedures. The static aspect here refers to "What" and the dynamic aspect refers to the "How". This research is expected to result in an intelligent interface mechanism incorporating aspects such as task correction.

Lowgren [47] discusses the development of a tool for managing expert system user interface, addressing conversational as well as model based expert systems. The tool developed is the "Ignatius" system and consists of two separate but communicating tools: the surface interaction manager and the session discourse manager. The domain system in Ignatius uses an Emycin rule base representation with a modified inference engine. This tool has been successfully tested to build small and simple user interfaces. Utilising this tool to develop user interfaces for life size expert systems would provide useful feed back on the future research to be carried out.

Interactive characteristic of multimedia which enables interaction [19], has been utilised in the development of the user interface presented in this chapter. The interactivity is both navigational and dynamical. Navigational interactivity allows the user to move sequentially through a series of predefined screens. The dynamic interaction allows the

user to work dynamically with the information, with situations changing in response to the choices made.

This chapter describes the development of a user interface for the material design system aided by a three character alphanumeric codification scheme to codify all the customer special requirements. The input to the material design system is in two stages. The input of the customer special requirements is done through the input screen designed based on this codification scheme. This enables input of over 230,000 different customer special requirements using a simple three stage hierarchical input as described in the following sections.

Visual development technique has been utilised in the development of the graphical user interface. An application can be designed, tested and implemented through visual development without writing any codes. Methods such as point and click, drag and drop and other visually oriented operations are utilised by the programmers to design and construct a program. Due to the following advantages [68], visual technique was utilised in the development of the graphical user interface:

- Provides immediate feed back and shows results of the feature and objects that are being manipulated.
- Faster and easier to learn.
- Allows more rapid application development.
- Provides improved program stability and integrity.
- Increases overall productivity.

To save development time and to enable use of existing standard utilities, a commercial software package (ProtoGen+) is utilised in the development of the user interface.

6.2 CODIFICATION SCHEME AND USER INTERFACE

The codification scheme developed to codify all the customer special requirements was also utilised in the design of the graphical user interface. The development of the codification scheme is described in details in chapter 3. This is a three character, alphanumeric codification scheme with a hybrid type code structure. The primary purpose of the codification scheme is to enable improvement in the efficiency of KEL, simplification in knowledge representation, reduction in computer storage space and search time. In addition to this the codification scheme also is utilised to develop a user friendly and simple graphical user interface as described in the following sections.

6.2.1 Input to the Material Design System

The material design system requires input of basic customer requirements as well as the special customer requirements. Based on these two types of requirements as input, the inference engine in the system processes the information by accessing various knowledge-bases and databases and generates appropriate steelmaking aim chemistries. The input of the basic information about the customer order could be easily achieved by developing an input screen which enables the input of the eight basic input parameters. The input of customer special requirements in not as straight forward as the basic input information. This is because the customer special requirements have a large number of possibilities from which the user has to make selection.

6.2.2 Codification Scheme Aided User Interface

The codification scheme has been effectively utilised to tackle this problem as described in this section. All the possible customer special requirements can be codified into the three character alphanumeric codification scheme, based on structuring the material design knowledge into a three level hierarchical structure. This hierarchical structuring of knowledge has been achieved during the KEL process. With this structuring it was possible to describe all the customer special requirements by three character codes. For each character in the code an input field is presented to the user which consists of all the possible values of corresponding customer special requirements. Thus a large number of (over 230,000) customer special requirements can be handled by the codification scheme due to the hybrid type structure of the codes. The hybrid type structure refers to the combination of the chain type and hierarchical type code structures.

6.3 DEVELOPMENT OF USER INTERFACE

This section describes the two input screens which are used to input the basic information about the order and the customer special requirements respectively. The second set of input screen utilises the codification scheme to input customer special requirements based on the hierarchical structure of the knowledge elicited during the knowledge elicitation process.

ProtoView dialogue editor is utilised in the design of the two input screens through point and click visual design methods. Basic features of the dialogue that can be modified are the controls within it and the styles of the dialogue itself. The controls can be moved, sized and aligned by selecting them with a mouse and dragging and dropping

the group of controls. Valid and invalid character filtering, formatted input for numeric values, built-in range checking, choice checking and table lookup functionality are some of the salient features of the input screens developed through the visual technique. The other features of the input screens include custom error checking and error display in response to user input and three-dimensional effects and window pattern to achieve impressive visual designs.

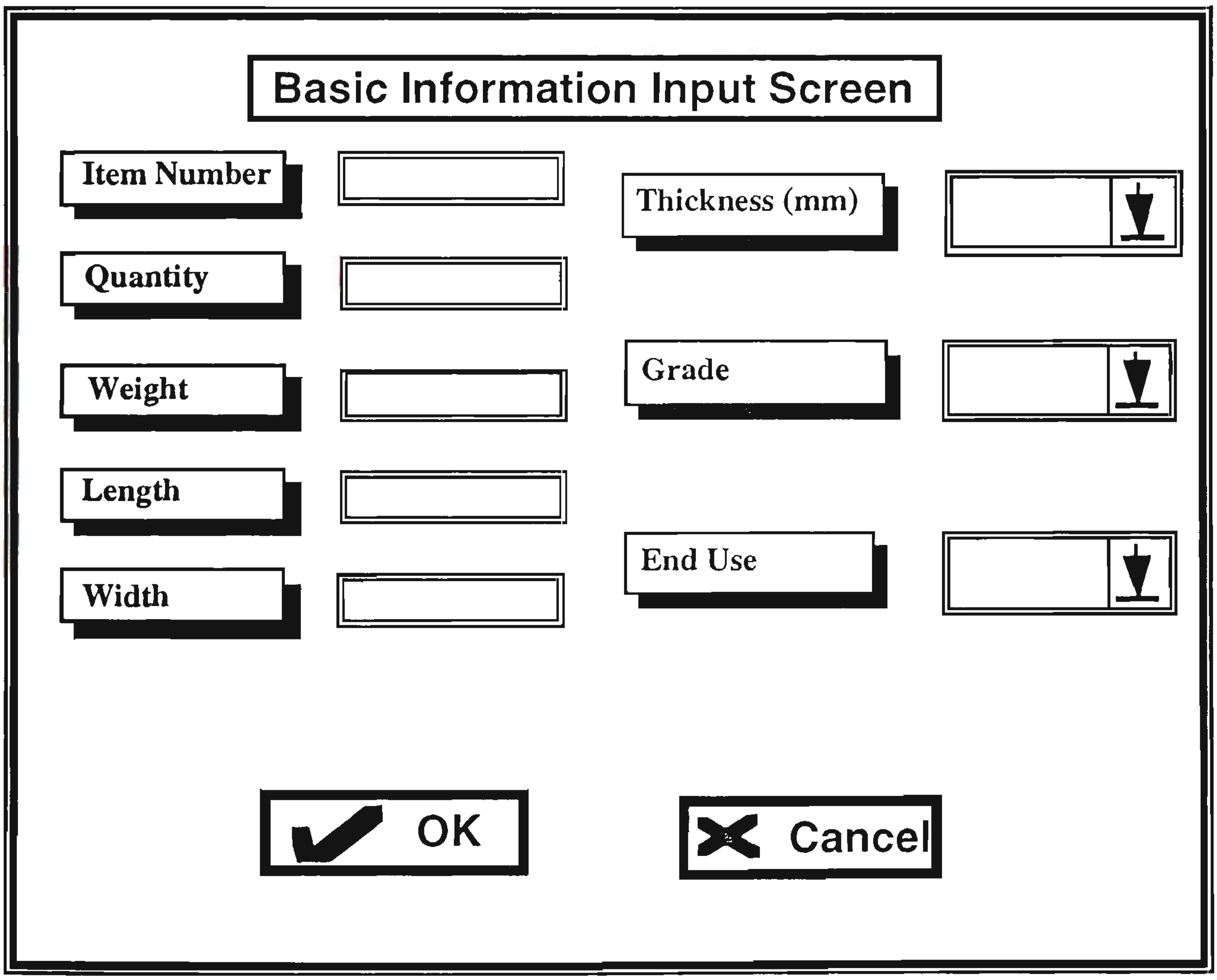


Figure 6.1 Input Screen 1

6.3.1 Input of Basic Information

In the first stage, the basic information which consists of details of the customer requirements such as the material standard, thickness, width, weight, length and end use of the steel plate required is input. An input screen is designed to enable the input of this basic information as illustrated in figure 6.1.

This input screen also utilises combo box fields (scroll down menu fields) to input the grade, thickness and the end use information which eliminates the need to type this information through the keyboard. Clicking on the drop down button in the combo box control, displays a scroll down menu consisting of all the strings. The user chooses the required value from this list and the application variable is updated with the new value every time the user changes the list box selection. Clicking on the "OK" button after inputting the basic information about the customer order pops up another screen to input customer special requirements as explained in the following section. Appendix A.1 shows the input screen for basic information.

6.3.2 Input of Customer Special Requirements

The second stage of input is through another screen which enables the input of the customer special requirements utilising three combo box fields corresponding to the customer special requirement types, the material types and the values of the special requirements respectively, as illustrated in figure 6.2. The first combo box field enables selection of the customer special requirement types which correspond to X_i's in equation 3.1. The second combo box field enables selection of the material types which

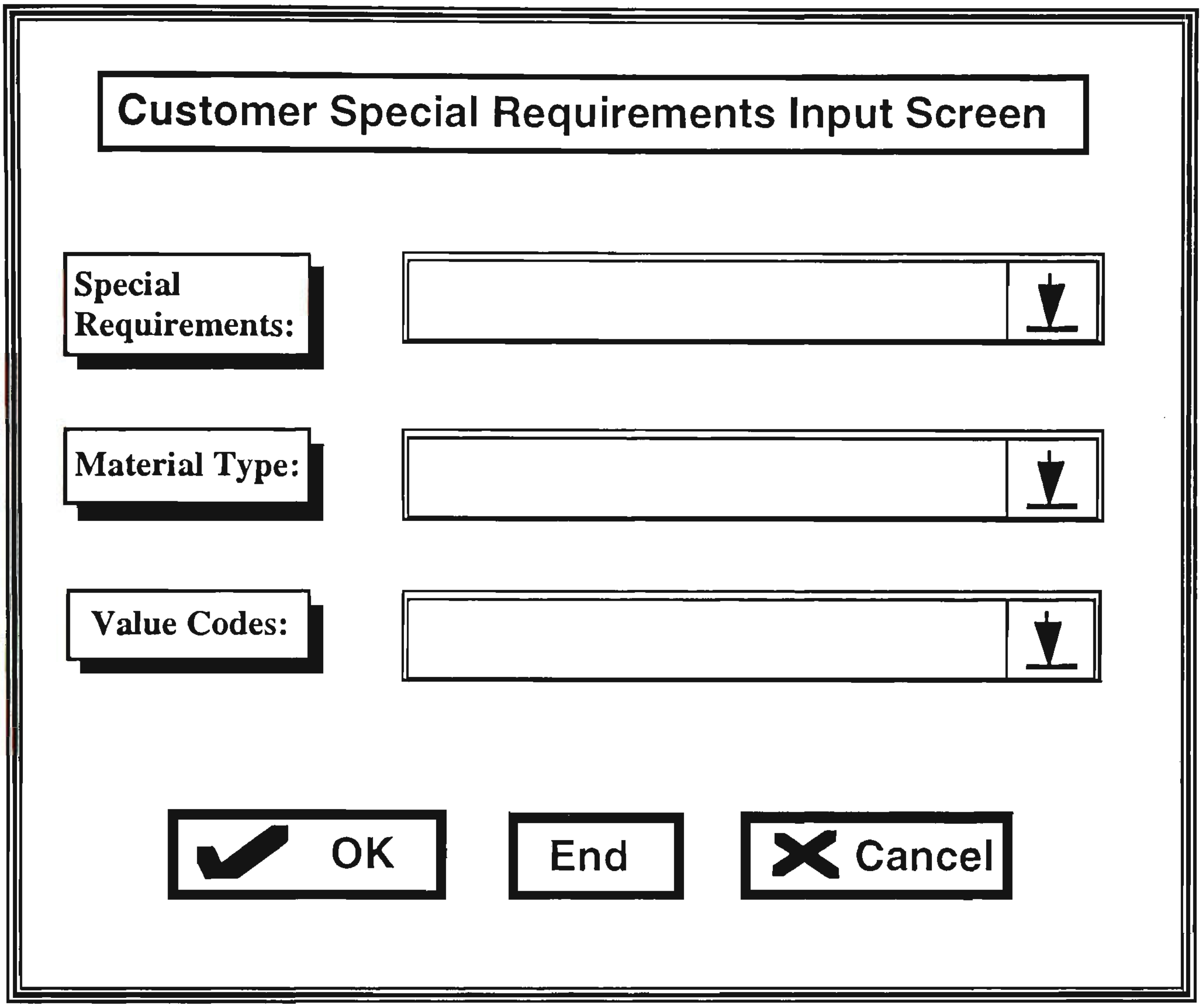


Figure 6.2 Input Screen 2

correspond to Y_j's in equation 3.1. Based on the selection of X_i's and Y_j's, appropriate values of Z_k's are loaded in the third combo box field corresponding to the value codes. The following example would clarify this further. If "Charpy" and "Structural Steel AS3678" is selected from the first two combo box fields, then the following set of values are loaded in the third combo box field:

- Longitudinal Charpys. Temperature = 0 or -15 °C. Minimum Absorbed Energy: Average of 3 Tests <= 27J, Individual <= 20J.

- Longitudinal Charpys. Temperature = 0 °C. Minimum Absorbed Energy: Average of 3 Tests > 27J and <= 48J, Individual > 20J and <= 40J.

- Longitudinal Charpys. Temperature = -15 °C. Minimum Absorbed Energy: Average of 3 Tests > 27J and <= 48J, Individual > 20J and <= 40J.

- Longitudinal Charpys. Temperature < -15 °C (-20 °C or -30 °C). Minimum Absorbed Energy: Average of 3 Tests > 27J and <= 48J, Individual > 20J and <= 40J.

- Longitudinal Charpys. Temperature < -15 °C (-20 °C or -30 °C). Minimum Absorbed Energy: Average of 3 Tests <= 27J, Individual <= 20J .

- Transverse Charpys. Temperature = 0 °C. Minimum Absorbed Energy: Average of 3 Tests <= 48J, Individual <= 40J.

- Transverse Charpys. Temperature > 0 °C (+10 °C or +20 °C). Minimum Absorbed Energy: Average of 3 Tests <= 48J, Individual <= 40J.

- Transverse Charpys. Temperature < 0 °C (upto -30 °C). Minimum Absorbed Energy: Average of 3 Tests <= 48J, Individual <= 40J.

These are the possible values of Z_k's (charpy testing requirements) for the combination of the X_i's (charpy) and Y_j's (AS3678). Thus the graphical user interface presents all

the possible values of the customer requirements for any combination of the X_i's and Y_j's , to the user to select from, through the scroll down menus.

Similarly in the case of Reduction in Area in Z direction (RAZ) testing and AS3678 type of steel, the set of values loaded in the corresponding scroll down menu is shown below:

- RAZ Minimum Average of 2 Tests = 15% to 25%
  RAZ Minimum Individual = 10% to 20%

- RAZ Minimum Average of 2 Tests = 15% or Less
  RAZ Minimum Individual = 10% or Less

Thus the combination of the three combo box fields enables input of all the customer special requirements utilising the codification scheme. Due to the hierarchical type structure of Z_k's, the number of value codes from which the values are to be selected does not become excessively large, hence simplifying the input of customer special requirements. The user is required to simply select three appropriate records from these scroll down menus. Clicking on the "OK" button pops up another dialogue box similar to the one displayed earlier to enable input of another customer special requirement. This could be continued to input all the customer special requirements and if there are no more customer special requirements, clicking on the "End" button would transfer the control to process the information using the inference engine of the prototype system. Figure 6.3 depicts the interaction of the two input screens. Appendix A.2 shows the input screen for the customer special requirements.

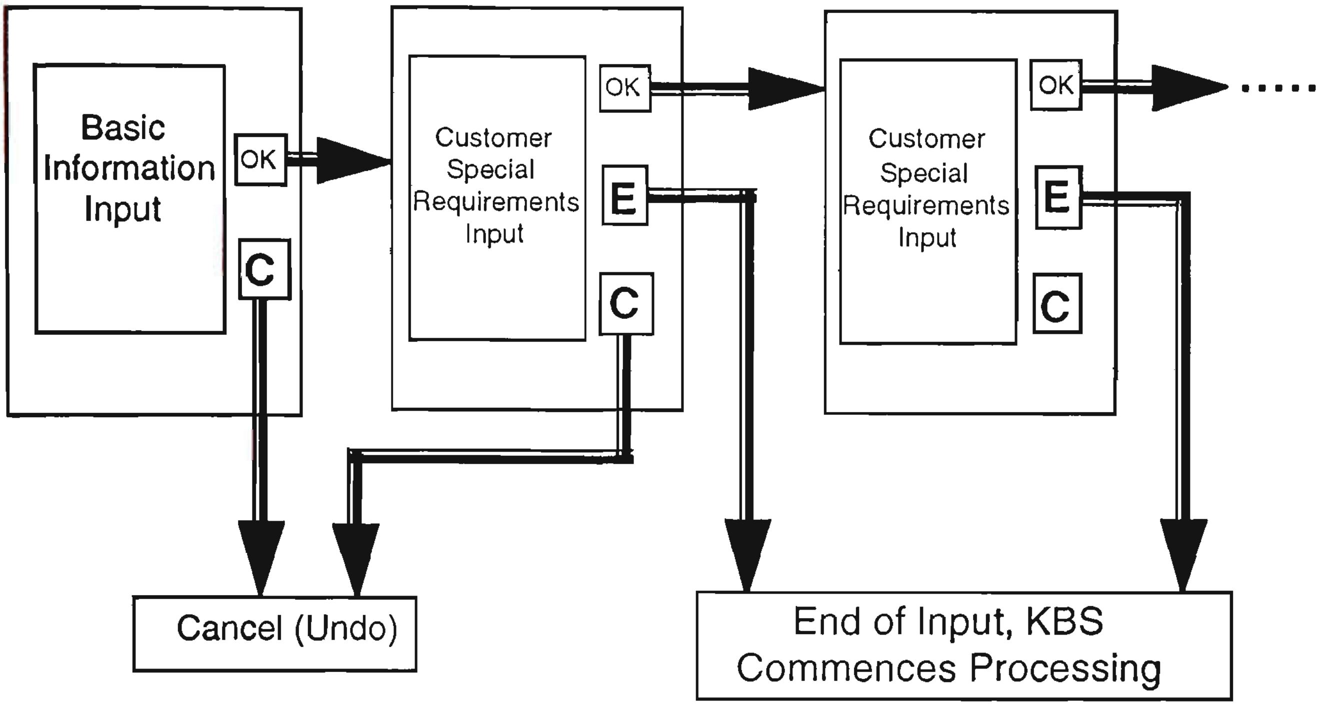


Figure 6.3 Schematic of the Graphical User Interface

6.4 SUMMARY AND CONCLUDING REMARKS

The information input through the two interactive input screens are converted into application variables and are used in processing the information in the inference engine of the prototype system. The customer special requirements input through the second set of input screens are converted into customer special requirements codes given by equation 3.1 and are then used in the prototype system to represent knowledge rules which include expert as well as heuristic rules. The user interface consisting of the two input screens for the basic information and the customer special requirements takes full advantage of the visual techniques available with ProtoGen+. In addition to making the system more user friendly and visually appealing, the interface developed also adds flexibility and sophistication to the prototype system for designing steel plates.

The GUI developed incorporates the features of a good GUI design explained in section 6.10. The important aspects which are incorporated into the GUI design are listed below:

- Simplicity through the two simple interactive screens which enable input of all the basic and special customer requirements.

- Minimum operator key strokes through the utilisation of scroll down menus.

- Ease of learning due to hierarchical structure in which the input fields are presented to the user.

- High speed of user task performance due to relatively small number of options presented to the user to choose from through the aid of the codification scheme.

- Low user error rate due to built in error and range checking facilities.

In addition to the above aspects, the GUI developed also results in simplification and conciseness in knowledge representation. The prototype material design system consists of a large number of knowledge rules which are represented in various knowledge-bases utilising the three character alphanumeric codification scheme. The GUI, which is also based on the same codification scheme, has three hierarchical fields corresponding to the major codes, sub group codes and the value codes respectively. Selecting the three fields through the interactive screen developed for inputting customer special requirements, converts the customer special requirements into CSRCs. These CSRCs are utilised in processing the customer special requirements and to obtain appropriate inferences through the inference engine of the prototype system. Thus the GUI

developed is closely linked to the knowledge representation, as both are based on the same codification scheme.

The simplicity of the graphical user interface thus developed is characterised by the shielding of the codification scheme for customer special requirements from the users. The users simply choose the requirements from the choices presented in a structured manner through the corresponding pull down menus and need not be concerned about the codification scheme and the corresponding customer special requirement codes.

The methodology presented in this chapter for developing user interface aided by the codification scheme could be applied to develop interfaces for knowledge-based systems in other fields also. By structuring the knowledge in a hierarchical structure and then codifying all the possible customer requirements which are the inputs to the knowledge-based system, the knowledge elicitation task as well as the task of successfully developing graphical user interfaces could be accomplished in a simplistic manner as described in this chapter.

If the domain knowledge in relatively complex fields could not be structured into a 3 level hierarchical structure, a four level hierarchical structure could be adopted to codify all the customer special requirements. Based on this four character alphanumeric codification scheme, the input screen could be developed having four hierarchical fields to input the special requirements, in contrast to the 3 field input screen described in this chapter.

CHAPTER 7

CHAPTER 7

REVIEW OF RESULTS GENERATED BY THE MATERIAL DESIGN SYSTEM

7.1 INTRODUCTION

The prototype material design system developed utilising hybrid approach has been tested with real life cases in this chapter to prove the usefulness of the methodology. This chapter also reviews the results generated by the system for sample cases along with a discussion on the short comings or limitations of the system. A sample prototype consultation is presented which explains the inputs to the system and the various outputs generated. The main software components of the system and the interfacing of these components into a single system is also discussed.

Feed-back from the experts about the performance of the system has been incorporated to improve the performance of the system and a methodology has been developed to obtain such feed-backs. At the end, the potential of the system in assisting the product development activities are discussed.

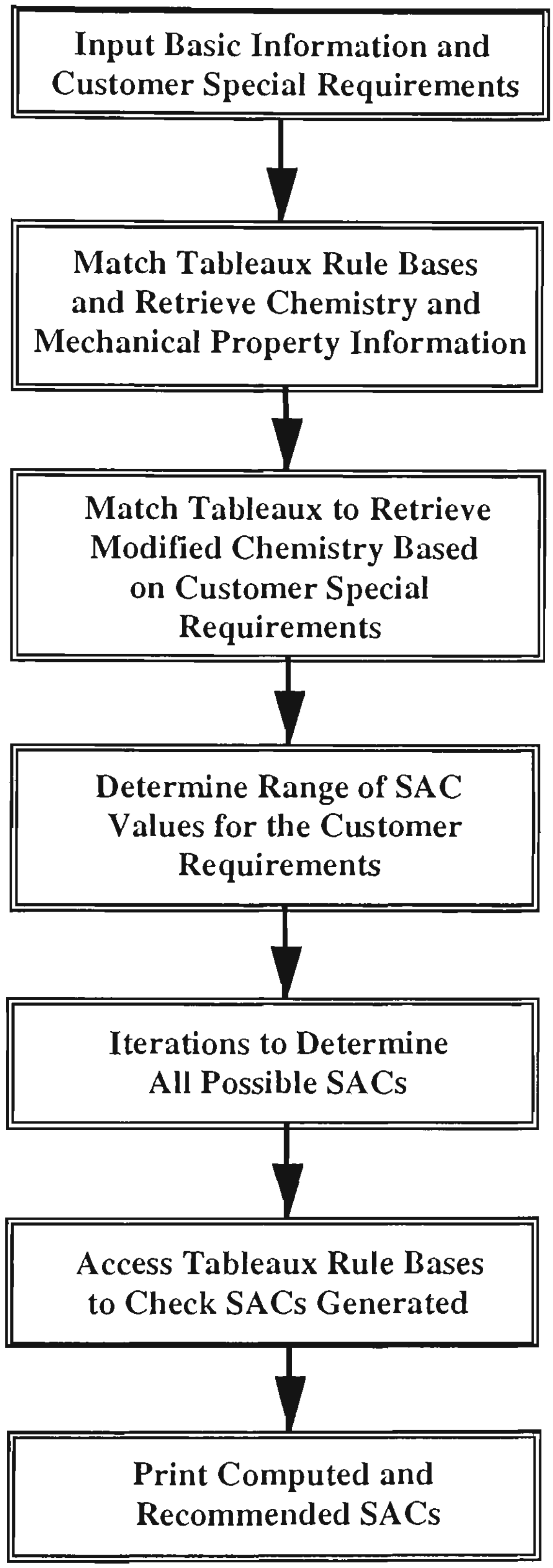


Figure 7.1 Main Steps in the Material Design System

7.2 SYSTEM IMPLEMENTATION

The material design system has been fully implemented in C language and generates steelmaking aim chemistries for a grade and thickness combination. It consists of over 4000 lines of codes and runs on an IBM compatible PC in windows environment. The graphical user interface developed for the system makes it more user friendly and enables quick and error free input of the customer requirements. The main steps in the implementation of the system are shown schematically in figure 7.1.

Basic information and customer special requirements are input through the two sets of input screens described in chapter 6. Chemistry and mechanical property information corresponding to the customer requirements are retrieved from various TABLEAUX rule bases by matching the corresponding TABLEAUX rule bases through call back to appropriate functions in the main program. The customer requirements of material standards could be the Australian material standards, international material standards or the customer special standards.

In the next step, the chemistry and mechanical property information obtained in the previous step is modified based on the customer special requirements. The input of this customer special requirements as explained earlier is through the interactive input screens which enable this input with the help of the three hierarchical fields corresponding to the customer special requirements.

The next step is to determine range of values for the steelmaking aim chemistries for the combination of the customer requirements and the increment values utilised in the iterative process. The iterations are carried out within this range of values of various

elements which are included in the steelmaking aim chemistry, starting from the minimum values in the range.

Iterative process based on the strategy explained in chapter 4 is then carried out to determine all the possible values of the steelmaking aim chemistries that are feasible for the combination of the customer requirements. Starting from the leanest chemistry and incrementing the values of the various elements in an order determined by the knowledge rules, the tensile and yield strengths that this chemistry could achieve is computed. This computation is based on the empirical models of the relationship between the tensile and yield strengths and the values of various elements in the steelmaking aim chemistry.

The iterative process explained above generates a large number of steelmaking aim chemistries that are theoretically feasible for the customer requirements. But all of these set of values are not practically feasible due to some limitations or constraints encountered in production units. The steelmaking aim chemistry values are hence scanned through a knowledge-base to filter out the set of values that are not feasible and final steelmaking aim chemistry list is generated which satisfies all the empirical models as well as the knowledge rules including expert and heuristic rules.

The final step in the material design system is to output the list of the computed and recommended steelmaking aim chemistry values to appropriate files. The output also consists of the chemistry limits, modified chemistry limits, range of steelmaking aim values along with the explanation for the customer special requirements.

7.2.1 Components of the System

The three main software components which constitutes the material design system as depicted in figure 7.2 include:

- The graphical user interface
- TABLEAUX rule bases
- The main system developed in C language

The graphical user interface is one of the most important components of the system and is designed utilising the software ProtoGen+. This enables quick and error free input of both basic and customer special requirements and makes the system more user friendly. This is the interface through which the user interacts with the system and is based on the codification scheme discussed in chapter 3. The details of development of the graphical user interface is described in chapter 6.

The knowledge represented in TABLEAUX is utilised in the material design system by accessing the knowledge, reason about it, and draw conclusions through the inference engine in TABLEAUX. The material design system utilises 13 different rule tables which have been represented in TABLEAUX. These rule tables are subsets of the four knowledge-bases described in chapter 4. Rules regarding the chemistry and mechanical property information, rules to modify the chemistry and mechanical property information and other knowledge rules required to process the customer requirements and to generate steelmaking aim chemistries are all contained in these rule tables. Sample TABLEAUX rule bases are shown in Appendix B. Over 500 rules required for

the inference engine of the material design system are represented in the TABLEAUX rule bases.

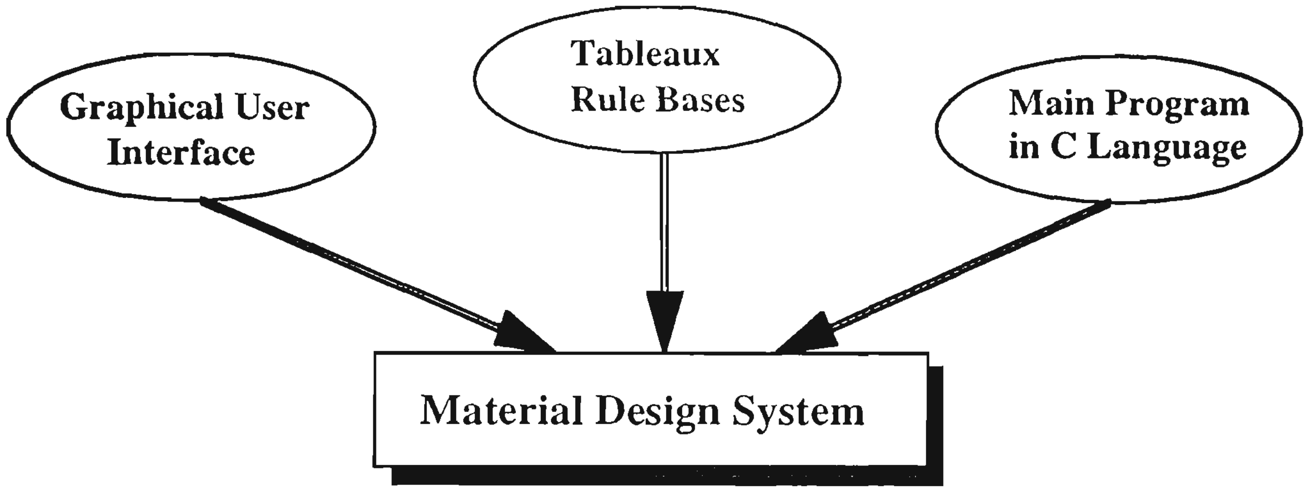


Figure 7.2 Main Components of the Material Design System

The main material design system is implemented fully in C language and consists of a number of functions. These functions perform various tasks such as matching the TABLEAUX rule bases, outputting information to appropriate files, etc. The main system also contains knowledge rules in the form of IF-THEN rules. The total number of rules including the rules in TABLEAUX and in the IF-THEN form are about 1000.

7.2.2 Interfacing the Three Software Modules

The three separate software modules described above are interfaced into a single system, as all the three modules are developed utilising C language. This is also one of the reasons to utilise C language in the development of the material design system. Commercially available software packages could be easily interfaced with systems developed in C language. Interfacing the graphical user interface with the main system,

required slight modification to the C program in DOS as the user interface was developed in C language in Windows environment.

TABLEAUX knowledge-bases could be implemented directly in the knowledge-based systems through program calls to the inferencing facilities within TABLEAUX. Since TABLEAUX internal routines are coded in C language, they could be easily transportable to other computer systems. The Windows Dynamic Link Libraries (DLLs) and header files provided in TABLEAUX allow embedded systems to use the TABLEAUX inference engine [64]. As the libraries were written in Borland C, can be used by Borland C applications such as the prototype material design system discussed in this thesis.

All parameters utilised to match the TABLEAUX rule bases and the returned decision values are character string pointers. The variables hence need to be converted into string variables before matching the TABLEAUX rule bases. Integer and float variables were converted to string variables to enable matching of TABLEAUX and were reconverted back into the original types after TABLEAUX matching.

7.3 PROTOTYPE CONSULTATION

7.3.1 System Inputs

Basic information in the customer requirements regarding the weight, length, thickness, grade and end use is input as shown in the input screen in figure 7.3. As explained in chapter 6, this input screen enables error free and fast input of the information utilising facilities such as range validation, error checking etc.

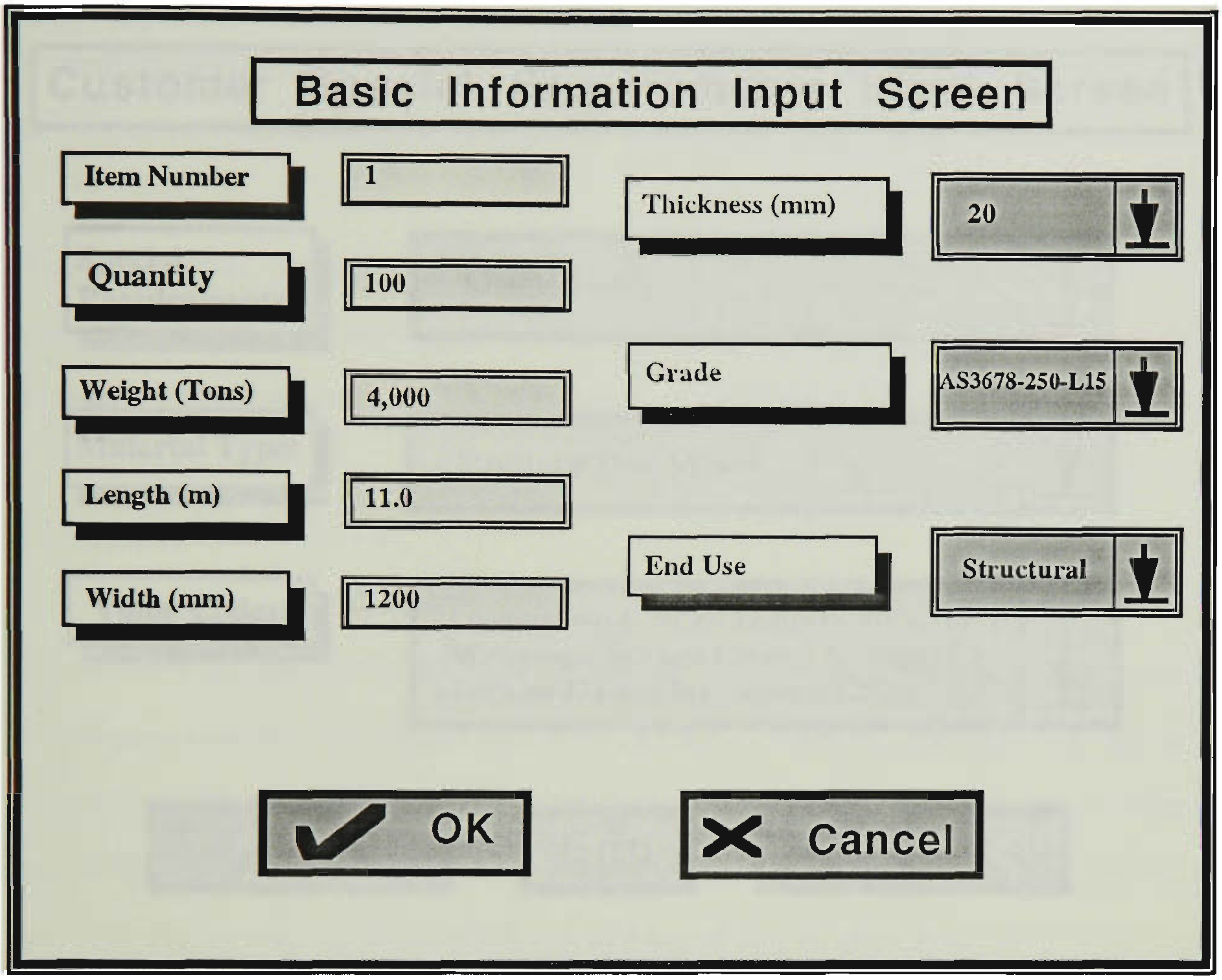


Figure 7.3 Basic Inputs for Prototype Consultation

Customer special requirements were input interactively through the input screen shown in figure 7.4. The customer special requirements for the prototype consultation consisted of charpy testing with values shown in figure 7.4.

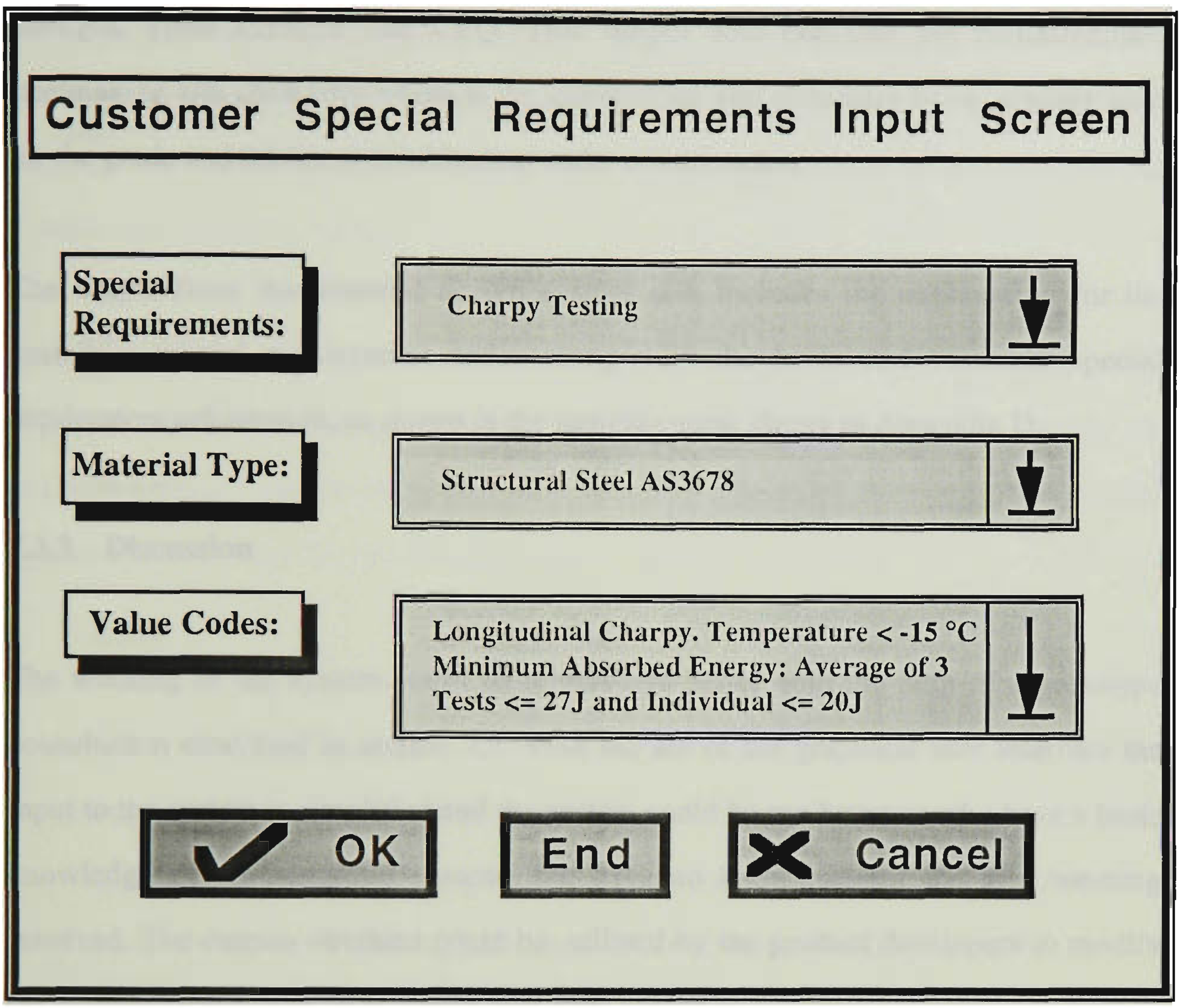


Figure 7.4 Special Customer Requirements Inputs for Prototype Consultation

7.3.2 System Outputs

The output generated by the system for the customer requirements, input in the above session are shown in Appendix D.2. The output consists of the chemistry (certification limits) based on the material standard required by the customer, the modified chemistry limits (modified certification limits) based on the customer special requirements and the range of values for the steelmaking aim chemistries. Another output generated consists of the computed steelmaking aim chemistries along with required and computed tensile

strength, yield strength and CEQ. This output also contains the recommended steelmaking aim chemistry which is the steelmaking aim chemistry being actually used for the grade and thickness combination under consideration.

The output from the material design system also includes the explanation for the customer special requirement codes along with the basic and customer special requirement information, as shown in the sample output shown in Appendix D.

7.3.3 Discussion

The working of the system could be understood better with the help of a prototype consultation described in section 7.3. With the aid of the graphical user interface the input to the system is simplified and the system could be run by users who have a basic knowledge of the computer systems but have no knowledge of the programming involved. The outputs obtained could be utilised by the product developers to modify the existing steel grades or to design new steel grades.

The number of steelmaking aim chemistries generated by the system for sample thickness of 20 mm and grade AS3678-250-L15 is 30. All of these could be utilised to cast slabs required to roll the customer requirements but with different degrees of desirability. This degree of desirability is obtained by applying fuzzy logic and computing fuzzy membership functions for chemistry, mechanical property, relative cost and complexity components. The methodology developed for the ranking of steelmaking aim chemistries is explained in chapter 5. The advantages of generating more than one steelmaking aim chemistry for customer requirements is to facilitate optimisation of the steelmaking aim chemistry. This could be accomplished by trading

off some parameters at the expense of other parameters. Due to inherent inaccuracy in the empirical models utilised in the prediction of tensile strength and yield strength values it is inevitable to obtain a range of steelmaking aim chemistry values that are feasible for a customer order.

Review of these outputs by the experts would enable checking the validity of the results obtained and the knowledge rules could be accordingly revised to incorporate the modifications as suggested by the experts. This would facilitate updating of the knowledge-bases and the system performance could be improved.

7.4 REVIEW OF RESULTS GENERATED

At the beginning, for a grade and thickness combination about 1500 various steelmaking aim chemistries were generated by the prototype material design system. Then more rules were included to reduce this number of steelmaking aim chemistries and at this stage the number of steelmaking aim chemistries generated vary between 14 and 30 for sample thicknesses which include 10 mm, 20 mm, 40 mm and 80 mm.

Prototype system developed during the research has been demonstrated to the users and the results generated match closely the results obtained by the experts in sample cases. The sample cases considered for prototype consultation consists of grade and thickness combinations generally encountered in actual practice. The structural steel grade AS3678 is the largest tonnage grade being produced by BHP Steel at Port Kembla. This grade accounts for about 70 % of the steel produced at Port Kembla. Thicknesses 10 mm, 20 mm, 40 mm and 80 mm are the most common thicknesses normally required by the customers. The prototype consultation for sample cases includes these thicknesses

and grade combinations and hence the prototype system has been demonstrated in all the representative cases. In all the 7 sample cases the prototype system has generated results similar to results generated by the experts. This demonstrates the potential of the research methodology developed.

The outputs generated by the prototype system for sample thicknesses of 10 mm, 20 mm, 40 mm and 80 mm are shown in Appendix D. The alternative steelmaking aim chemistries thus generated were then scanned through a database of details of steelmaking aim chemistries being presently used in the plant at BHP Slab and Plate Products Division. This was done by down loading the details of the existing steelmaking aim chemistries from the Technical Specification System (TSS) database being used in the plant. Except in one case (Thickness = 20 mm) it was found that the steelmaking aim chemistries generated by the system were in fact the same as the one currently being used. In case of 20 mm thick plate the system recommended two steelmaking aim chemistries (0361 & 0638). However with more precise rules it is possible to get a single steelmaking aim chemistry recommended for each grade and thickness combination from the list of computed steelmaking aim chemistries. Table 7.1 summarises the results generated for the sample cases.

As end use is important factor which affects the steelmaking aim chemistries, the output generated by the prototype system could be improved further by extending the knowledge-bases to include more rules corresponding to the end use of the steel plates required. For example the knowledge-bases could be extended by including more rules such as:

If End Use is Sour Service

Then H_{max} = 1.9ppm and

S_{max} = 0.003%

Thus extra features could be easily incorporated in the prototype system which demonstrates that the KEL approach could be extended to enable building a full scale system.

Table 7.1 Results Generated by Material Design System for AS3678-250 Grade

Thickness (mm)	No of SACs Generated	Recommended SAC	Remarks
10	17	One	Agrees with TSS
20	30	Two	One Agrees with TSS
40	19	One	Agrees with TSS
80	14	One	Agrees with TSS

7.5 LIMITATIONS OF THE SYSTEM

Most of the knowledge rules in the prototype material design system at this stage are regarding the basic input parameters: thickness and material standard. The system could be enhanced by including more rules regarding other basic input parameters such as the end use, length, width and weight. Presently AS3678-250 grade and its derivatives are the only grades considered in the system and hence the system is restricted to the recommendation of steelmaking aim chemistries for these grades only. Other material standards could be included in the system by acquiring appropriate rules from the experts corresponding to these standards.

Processing and chemistry are the two important components in steel product development which are to be considered simultaneously. Steelmaking aim chemistries, in this work are determined for the normal "as rolled" process. Other rolling processes such as normalising or control rolling has not been considered at this stage. These processes have the potential to roll steel plates utilising a leaner steelmaking aim chemistry than that used for the "as rolled" process. However, the cost of these processes is higher than the cost of the "as rolled" process. This aspect could be included in the full scale material design system by incorporating appropriate expert and heuristic rules corresponding to the rolling processes other than the "as rolled" process. However, this is beyond the scope of this thesis.

The empirical models based on the statistical data utilised in the system are characterised by an error of the magnitude of ± 20 to ± 40 MPa. This error is mainly due to the variability present in various parameters related to testing and chemistry requirements. The error of this magnitude results in a wide range (14 to 30 steelmaking aim chemistries for the sample cases) of possible steelmaking aim chemistries for any combination of grade and plate thickness required by the customer. This also makes it desirable to use more heuristic or thumb rules to reduce the number of steelmaking aim chemistries generated by the prototype system. Empirical Models with better error rates would improve the outputs generated by the prototype system as well would reduce the number of steelmaking aim chemistries generated. Metallurgical models which have slightly better error rates could be considered instead of the empirical models for better results. However, these models require the values of various process parameters to estimate the tensile and yield strength values. With the present approach of determining steelmaking aim chemistries, these process parameters are outside the scope of present research.

Expert as well as heuristic rules in various knowledge bases are normally applicable to a range of steel plate thicknesses. This means that the rules are applicable to different degrees depending on the thickness of the steel plate required by the customer. The grade history database has performance data for the grade and plate thickness combinations made in the past. If the grade required by the customer has not been made in the past, there is no data which can be used in processing the customer requirements and hence the prototype system will fail to generate any SACs. Empirical models are based on the statistical data in the grade history database. In cases where there is less number of records, the models would not be very accurate and hence the results generated may not be very reliable. Due to these reasons the prototype system would not generate very reliable results in the case steel grades which are relatively new.

7.6 SUMMARY AND CONCLUDING REMARKS

The results generated by the prototype material design system for the sample cases demonstrate the potential of the methodology developed to deal with steel plate design. The methodology utilising the mathematical modelling and the knowledge-based system approach could be effectively utilised to aid the metallurgists in designing or modifying steel grades based on the customer requirements. It is the quality of the rules in the knowledge-bases which reflect the performance of the system and it is possible to incorporate more rules to improve the performance of the system.

Full scale material design system based on the prototype system developed could prove to be an important tool to the metallurgists at product development section. The material design system thus developed could assist the metallurgists in the modification of

existing steel grades or the design of new grades. The cumbersome task of iterations involving enormous computations could be successfully handled by the system. The system could utilise expert knowledge and heuristic knowledge, based on the rules of thumb, from a group of experts. Due to these reasons the material design system is expected to perform better than the experts with manual calculations. The steelmaking aim chemistries generated by the material design system if reviewed critically may lead to a radical change in the current philosophy being pursued in the determination of the steelmaking aim chemistries. It may also initiate rethinking about the question - "Whether the steelmaking aim chemistries being used are the optimum one?"

CHAPTER 8

CHAPTER 8

CONCLUSION

8.1 SUMMARY OF RESEARCH UNDERTAKEN

8.1.1 Benefits of Applying AI Techniques

Design of steelmaking aim chemistries is very important, as it affects the productivity of various production units such as ladle injection station, vacuum degassing station, the continuous casting machine, etc., in a steel making organisation. Customer enquiries or orders are analysed by a group of experts to decide whether the customer specifications could be met. If it is possible to meet the customer requirements, then the next task is to decide the steelmaking aim chemistry and the processing required to obtain the steel that satisfies the customer requirements. The time taken to carry out these functions is of the order of few days in general and in some cases even few weeks, if the steel plate required is associated with some special customer requirements.

The time taken to answer the customer requirements could be reduced considerably if some of the functions could be automated by the application of artificial intelligence techniques. Dependence on experts could be reduced and consistent designs could be obtained every time due to the application of the AI techniques in conjunction with the mathematical modelling approaches. The introduction of such techniques would

improve the competitive edge of the organisation through reduced time required to reply to customer enquiries and increased customer satisfaction.

The benefits from the prototype system developed during this research can be well understood by comparing this system with the manual system. In the manual system the product developer (expert metallurgist) considers some combination of various elements only due to the limitations of time and due to the difficulty in handling the complex computations associated, if all the feasible elements were considered. Depending on the customer special requirements a number of experts have to be consulted before generating SACs which satisfy all the customer requirements. This process takes a long time especially when one of the experts is not available. Decision cannot be taken quickly in such situations and this may affect the delivery schedule. The design obtained may not be optimum one as all the feasible alternatives are not considered due to the limitation of the manual system. The design process in addition is not consistent. Depending on the expert available at that instant of time, the design process would vary considerably.

All the above limitations can be successfully eliminated with a hybrid type of decision support system explained in this thesis. There are no limitations on the extent of computations involved. All the feasible elements along with various increment values could be tried, thus making it sure that there are no potential solutions untested. This makes the SAC generated the optimum one. As the knowledge from all the experts are elicited and compiled in various knowledge bases, there is no dependence on the experts as in the case of the manual system. As all the concerned experts have validated the knowledge bases, the results generated by the system would represent the solution,

which is agreeable to all. The system would generate the same solution every time and hence there is consistency in the results generated by the system.

8.1.2 Summary of Research Tasks Accomplished

This thesis presents development of a methodology to design the steelmaking aim chemistries by utilising mathematical and knowledge-based approaches. A hybrid approach has been developed to design the steelmaking aim chemistry which utilises various knowledge-bases, various empirical models and the grade history databases having the performance data for the grades made in the past. As a first step in this direction, a new methodology for KEL is developed to improve the efficiency of KEL and to simplify the knowledge representation. The KEL methodology developed utilises codification scheme, paper models and non-interview techniques to efficiently elicit the material design knowledge. The KEL methodology also reduces the computer storage space and search time considerably.

Testing of the prototype system with real life cases has proved the potential of methodology developed. The methodology has the potential to assist the metallurgists in the design of new plate grades or the modification of existing plate grades by taking up the cumbersome task of iterations involving enormous computations and by utilising the expertise of a group of expert metallurgists including their heuristic knowledge.

Ranking of various steelmaking aim chemistries utilising fuzzy membership functions is also accomplished in this research. A modified methodology has been developed to rank the steelmaking aim chemistries based on chemistry requirements, mechanical property requirements, relative cost and complexity factors. New methodology has been

developed to obtain fuzzy membership components for relative cost and complexity factors.

A user friendly graphical user interface has been developed for fast and error free input of customer requirements based on the codification scheme developed during the KEL process. This has been achieved through two sets of interactive screens to input the basic customer requirements and the special customer requirements respectively.

8.1.3 Benefits from the Prototype System

The important benefits in developing steel products from the prototype system developed during this research are summarised below :

- Assistance to metallurgists in the development of new plate grades or in the modification of existing grades by
  - Taking up the cumbersome task of iterations involving large calculations and
  - Utilising the expertise of a group of experienced metallurgists
- Time required to determine steelmaking aim chemistries is of the order of few minutes resulting in a quicker response to customer enquiries.
- Use by non-experts, resulting in reduced dependence on expert metallurgists in the determination of steelmaking aim chemistries.
- Exploring the possibility of considering potential steelmaking aim chemistries which have been generated by the system.
- Initiate re-thinking about the whole process of generation of steelmaking aim chemistries.

The application explained above is not an isolated industrial application. There are a number of similar applications such as design of various ferrous and non-ferrous alloys where this methodology can be successfully applied to generate results, which satisfy a set of input requirements. Tasks in the design field which mainly depend on the intuition of experts as well as the rules of thumb along with complex computations can be successfully accomplished with the aid of hybrid systems which combine the benefits of knowledge bases and the computational power available in today's computers. If these tasks are undertaken manually the time required would be too much and hence may not be practical due to the iterative nature of the task. The iterative process enables trying out all the potential alternatives before arriving at the recommended results. The knowledge from a group of experts is required in generating results in complicated design processes such as the design of SACs. The dependence on the experts results in delays in the design process. These limitations of dependence on experts can be reduced considerably with the aid of a hybrid system. The methodology developed can also be successfully applied in the processing of various materials such as aluminium and ferro alloys.

The second part of the research in the thesis utilises fuzzy logic to rank alternative SACs in the order of desirability. This process of ranking of various alternatives by considering various constraints has several potential industrial applications. There are industrial applications where a number of alternative solutions are feasible with different desirability factors associated with them. In many of such applications some sort of trading off is involved. For example a cheaper solution is enough for an application which is not very critical. In the case of steel required for an application such as dead weight, the tensile and yield strengths of the steel are not very important. This means that, if the steel grade could be made cheaper by sacrificing the strength

parameter, it is not going to affect the functional aspect of the steel. This type of trading off could be accomplished utilising fuzzy logic as explained in chapter 5.

8.1.4 Implementation of the system

The material design system has been fully implemented by developing a software module for generating the alternative steelmaking aim chemistries and another module for ranking the steelmaking aim chemistries generated by the first module. Both the modules are developed in C language, mainly because it is possible to interface various commercial software packages with a system developed in C. The first module has three software components interfaced into a single system which includes the TABLEAUX tool for knowledge representation, Protogen+ tool for user interface development and the main material design system developed in C language in DOS environment.

The second module as mentioned above is a stand alone system which reads the steelmaking aim chemistries generated by the first module, computes various fuzzy membership functions and the weighted sum membership function and finally generates the ranked steelmaking aim chemistries. This module utilises statistical data from the grade history database obtained through a statistical software package, SAS. The systems developed were tested by taking real life sample cases and the results generated have proved the potential of the methodology developed.

During this project most of the research time was spent at the Central Laboratory in BHP Slab & Plate Product Division, Port Kembla. Staff members including experts at specifications and product development sections were consulted extensively on a

number of occasions mainly to elicit material design knowledge and to collect various data required for the development of the prototype system.

KEL approach developed utilising the three character alphanumeric codification scheme in combination with the knowledge representation tool TABLEAUX, resulted in simplification in knowledge representation for the complex problem of designing the steelmaking aim chemistries. The hybrid system developed for material design utilising mathematical modelling and knowledge-based approaches can be considered as the first of its kind, where the mathematical modelling enables iterations involving enormous computations and the knowledge-based approach enables utilising the expert as well as heuristic knowledge from a group of experts to successfully determine the steelmaking aim chemistries. There is no sound methodology available in the literature reviewed for developing such a hybrid system.

8.2 RECOMMENDATION FOR FUTURE RESEARCH

Summaries of major tasks identified for future research are discussed briefly in the following sections.

8.2.1 Development of Fuzzy Membership Functions

Steel making is a field characterised by interaction of numerous factors and complex interrelationship between these factors. An attempt has been made in this thesis to outline a simple methodology to model this complex field by the application of fuzzy logic to rank the steelmaking aim chemistries. There is further scope to undertake future research to improve the methodology of ranking.

8.2.1.1 Handling Skewed and/or Insufficient Data

The membership functions for mechanical properties and chemistry, developed in the preceding section are based on the assumption that the statistical data being considered is normally distributed and that there is no skewness present in the data. The work done by other researchers [91-92] and [97-98] is also based on the above assumption. However, this is not always true in actual industrial situations. The data may be associated with skewness and the sample size may not be large enough and thus the assumption that the data is normally distributed is not always true. Developing membership functions in such situations is very difficult because of the inadequacy of the existing procedures to deal with this problem. Developing a methodology to deal with such data and to compute the membership functions is therefore of great significance for the success of the fuzzy systems being developed.

The alternate approach that could be utilised to deal with this problem include, combining subjective information obtained from the experts regarding the skewed/insufficient data along with the objective information (statistical data) to compute the membership functions. This approach has been successfully applied to a geotechnical problem by Valliappan *et. al* [90]. The approach utilises fuzzy calculus, the program evaluation and review technique and the concept of relativity theory. The knowledge inputs from the experts are the subjective information and the statistical data with known probability functions are the objective information used by the researchers. The subjective part is transformed into a fuzzy set by applying a fuzzifier characterised by its kernel [104].

Brown [8] has also described somewhat similar process of merging fuzzy and crisp information. In this work, the objective probabilities are fuzzified based on the subjective information. The subjective information is expressed by two factors: "Gravity" and "Effect" and is dealt by fuzzy set theory. Principle of maximum entropy has been utilised in this work to deal with the objective information by constructing unbiased probabilities.

To deal with the real life situation where skewed and/or insufficient data is available, the approach of combining objective and subjective information could be further researched. A methodology based on this approach would enable improvement in the process of computation of fuzzy membership functions.

8.2.1.2 Relative Cost and Complexity Components

Fuzzy membership function component of relative cost has been determined based on the cost of adding alloying elements and the cost of the processing required to meet customer requirements. Equations have been developed to determine the cost of adding alloying elements and the cost of processing. Detailed study of various processes and their relative impact on the cost factor could be undertaken to improve the methodology of ranking. Similarly detailed study on the impact of adding various elements on the relative cost factor could lead to an improvement of the methodology to rank the steelmaking aim chemistries.

Determination of complexity factor in the fuzzy membership function is another area which has scope for undertaking further research. The methodology presented in this thesis could be researched further and improved to obtain fuzzy membership component

for the complexity factor. Factors affecting the complexity in steel making have been identified in this work, but further detailed analysis is required to determine the relative impact of these factors on the fuzzy membership function component. Improvement in these two methodologies to determine the fuzzy membership functions would result in ranking the steelmaking aim chemistries in a more realistic manner.

8.2.1.3 Choice of the Values of the Weighting Coefficients

The weighting coefficients (βs) reflect the relative importance of the four components utilised in the computation of the WSMF. As discussed in chapter 5, the ranking process mainly depends on the values of the four weighting coefficients. The values β_1 = 0.40, β_2 = 0.30, β_3 = 0.18 and β_4 = 0.12 utilised in sample computation of ranked steelmaking aim chemistries were obtained during "preliminary" interviews with the expert metallurgists and hence may not realistically reflect the relative importance of the four components nor their optimum values. A detailed study on the relative impact of the values of βs in the ranking process is to be undertaken to achieve a further improvement in the results generated. A more in depth knowledge elicitation could result in a better understanding of the relative importance of the four components in the ranking process and hence proper choice of the four weighting coefficients.

8.2.2 Inclusion of Processing Domain in the Material Design System

Processing of the molten steel produced at the basic oxygen steelmaking furnace and controlling process parameters at the other production units such as the casting machine and the rolling mill are vital factors in the process of determining steelmaking aim chemistries. It is possible to meet requirements from various customers by using a single

steelmaking aim chemistry and by utilising various processing such as ladle injection, vacuum degassing, thermo-mechanical control rolling, normalising, etc. This factor is not considered in the present research for the purpose of making the project manageable. Thus, processing is an integral part in the process of designing steel plates and hence has to be considered jointly along with the determination of steelmaking aim chemistries.

A knowledge-base module containing rules corresponding to processing domain could be elicited from the experts and incorporated into the material design system to broaden the scope of the system. This knowledge-base module could contain knowledge rules including expert as well as the heuristic rules based on the intuition of experts and the rules of thumb. Presently knowledge-base modules contain rules mainly in the chemistry domain.

8.2.3 Optimisation of Steelmaking Aim Chemistry

An integrated system could be developed which consists of an additional module to generate optimum steelmaking aim chemistries for any standard rolling schedule with known values of strain, strain rates, temperature, interpass time and slab thickness. The output from the system described in this thesis could be utilised as input to this second module. Metallurgical parameters such as the final grain size, precipitation and phases can be determined by this module for a standard rolling schedule for the input of steelmaking aim chemistries determined by the material design system. The knowledge-based component of the module could contain knowledge rules including heuristic rules to determine the metallurgical parameters corresponding to the basic process routes. These metallurgical parameters along with appropriate knowledge-bases can be utilised

to realistically predict the achievable mechanical properties corresponding to the steelmaking aim chemistries utilising metallurgical models.

The output from the proposed module is the achievable mechanical properties and the corresponding steelmaking aim chemistries. This output can be utilised to assist the product development metallurgists in the selection of optimum steelmaking aim chemistries for any combinations of customer requirements from metallurgical point of view.

8.2.4 Improvement in the Iterative Strategy

Knowledge-base module KB IV consists of rules to determine the incremental values for the elements to be added in the steelmaking aim chemistry. It also contains the aim chemistry restrictions. The selection of elements to be included in the aim chemistry and the sequence in which the elements are to be included are presently based mainly on the heuristic knowledge of the experts.

Systematic study of the effect of adding various elements in the steelmaking aim chemistries vis a vis cost of adding unit amount of the element and the corresponding increase in tensile and yield strengths could be researched further. This would enable optimum selection of elements for inclusion in the aim chemistry and priorities could be determined for the various elements based on the cost, strength and other relevant factors impacting on the design process.

8.2.5 Interfacing SAS Software Package into the Material Design System

Statistical data from the grade history database has been extensively utilised in the prototype material design system developed. Mean and standard deviation values of chemistry and mechanical properties for any combination of grade and thickness from the database are utilised in the computation of the corresponding fuzzy membership functions. Based on this individual membership functions the weighted sum membership functions are computed which enable the ranking of the steelmaking aim chemistries.

Statistical analysis software, SAS has been utilised to obtain the mean and standard deviation values required in the above computation. The values of mean and standard deviation are obtained by running programs in SAS language off line and are then input to the material design system to enable further processing. Interfacing the material design system with SAS software would result in less time taken to process the customer orders and also would result in simplification of the system. This aspect of interfacing could be further researched and a knowledge-base could be incorporated into the material design system which identifies appropriate grades nearest to the grades required by the customer. Once the appropriate grades have been identified, SAS programs could be run from the main program and the values of statistical variables required by the system could be retrieved and utilised in the main system for further processing.

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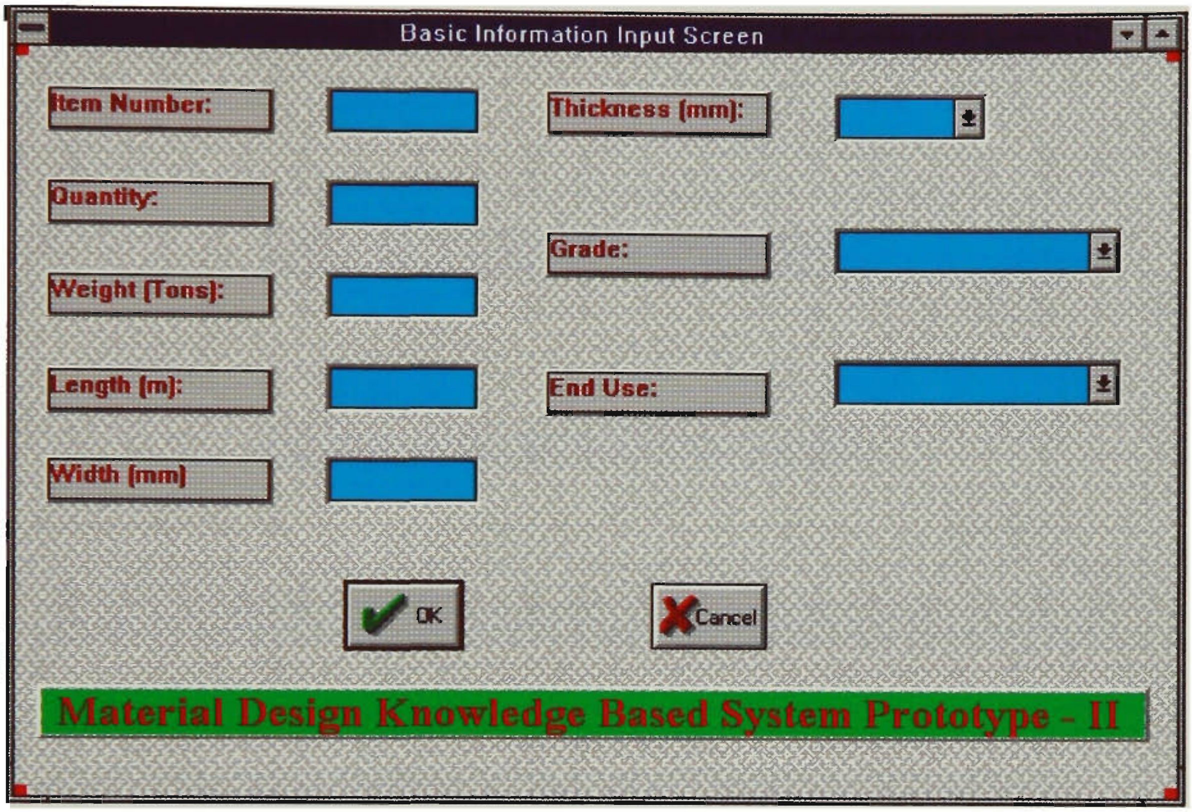
APPENDIX A

INPUT SCREENS

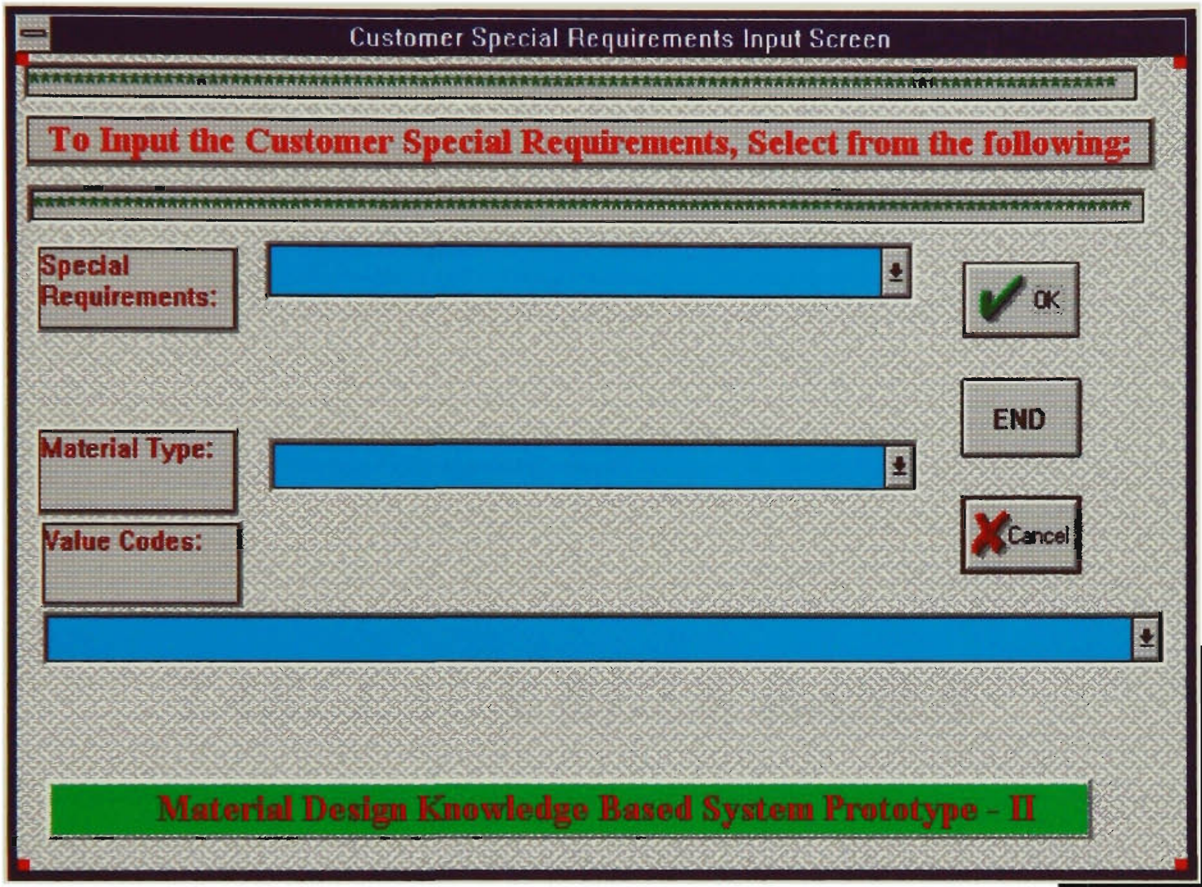
APPENDIX A.1

Input Screen for Basic Information



APPENDIX A.2

Input Screen for Customer Special Requirements



APPENDIX B

TABLEAUX RULE BASES

APPENDIX B

Explanation for the terms used in Appendix B

Chemical elements are denoted by the first four characters in their name. Letter "l" and "u" at the beginning of the parameters indicates the lower and the upper limits or the minimum and the maximum values respectively of various elements considered in the determination of steelmaking aim chemistries. For example "l carb" and "u carb" denotes the lower and upper values of carbon respectively. The term "c3" denotes the carbon equivalent or "CEQ3".

The terms "AS3678 200", "AS3678 250", "AS3678 250Z", "AS3678 250 L15", "AS3678 300", "AS3678 300 L15", "AS3678 350", "AS3678 350 L15", "AS3678 400", "AS3678 400 L15", "AS3678 WR 350 1" and "AS3678 WR 350 1L0" denotes various grades in the Australian structural steel standard AS3678. In Appendix B.2 "l ysreq", "l tsreq" and "l el" denotes the lower value of the yield strength, tensile strength and the elongation respectively. In Appendix B.3 "T SIZE", "avg ener" and "ind ener" represent the test piece size for charpy testing, the average energy and the individual energy respectively.

APPENDIX B.1

Tableaux Rule Base for Chemistry Details for AS3678 Material Standard

	Rule 1	Rule 2	Rule 3
GRADE	AS3678 200	AS3678 250	AS3678 250Z
l carb	0	0	0
u carb	0.15	0.22	0.22
l sili	0	0	0
u sili	0.35	0.55	0.55
l mang	0	0	0
u mang	0.6	1.7	1.7
l phos	0	0	0
u phos	0.03	0.04	0.04
l sulp	0	0	0
u sulp	0.03	0.04	0.04
l crom	0	0	0
u crom	0.3	0.3	0.3
l nick	0	0	0
u nick	0.5	0.5	0.5
l copp	0	0	0
u copp	0.4	0.4	0.4
l alum	0	0	0
u alum	0.1	0.1	0.1
l tita	0	0	0
u tita	0.04	0.04	0.04
l moli	0	0	0
u moli	0.1	0.1	0.1
l niob	0	0	0
u niob	0	0	0
l vana	0	0	0
u vana	0.015	0.015	0.015
l c3	0	0	0
u c3	0.25	0.45	0.45

	Rule 4	Rule 5	Rule 6
GRADE	AS3678 250 L15	AS3678 300	AS3678 300 L15
l carb	0	0	0
u carb	0.22	0.22	0.22
l sili	0	0	0
u sili	0.55	0.55	0.55
l mang	0	0	0
u mang	1.7	1.7	1.7
l phos	0	0	0
u phos	0.04	0.04	0.04
l sulp	0	0	0
u sulp	0.04	0.04	0.04
l crom	0	0	0
u crom	0.3	0.3	0.3
l nick	0	0	0
u nick	0.5	0.5	0.5
l copp	0	0	0
u copp	0.4	0.4	0.4
l alum	0	0	0
u alum	0.1	0.1	0.1
l tita	0	0	0
u tita	0.04	0.04	0.04
l moli	0	0	0
u moli	0.1	0.1	0.1
l niob	0	0	0
u niob	0	0	0
l vana	0	0	0
u vana	0.015	0.015	0.015
l c3	0	0	0
u c3	0.45	0.45	0.45

	Rule 7	Rule 8	Rule 9
GRADE	AS3678 350	AS3678 350 L15	AS3678 400
l carb	0	0	0
u carb	0.22	0.22	0.22
l sili	0	0	0
u sili	0.55	0.55	0.55
l mang	0	0	0
u mang	1.7	1.7	1.7
l phos	0	0	0
u phos	0.04	0.04	0.04
l sulp	0	0	0
u sulp	0.04	0.04	0.04
l crom	0	0	0
u crom	0.3	0.3	0.3
l nick	0	0	0
u nick	0.5	0.5	0.5
l copp	0	0	0
u copp	0.4	0.4	0.4
l alum	0	0	0
u alum	0.1	0.1	0.1
l tita	0	0	0
u tita	0.04	0.04	0.04
l moli	0	0	0
u moli	0.1	0.1	0.1
l niob	0	0	0
u niob	0	0	0
l vana	0	0	0
u vana	0.015	0.015	0.015
l c3	0	0	0
u c3	0.48	0.48	0.48

	Rule 10	Rule 11	Rule 12
GRADE	AS3678 400 L15	AS3678 WR 350 1	AS3678 WR 350 1L0
l carb	0	0	0
u carb	0.22	0.14	0.14
l sili	0	0.15	0.15
u sili	0.55	0.75	0.75
l mang	0	0	0
u mang	1.7	1.7	1.7
l phos	0	0.055	0.055
u phos	0.04	0.16	0.16
l sulp	0	0	0
u sulp	0.04	0.04	0.04
l crom	0	0.35	0.35
u crom	0.3	1.05	1.05
l nick	0	0	0
u nick	0.5	0.55	0.55
l copp	0	0.15	0.15
u copp	0.4	0.5	0.5
l alum	0	0	0
u alum	0.1	0.1	0.1
l tita	0	0	0
u tita	0.04	0.04	0.04
l moli	0	0	0
u moli	0.1	0.1	0.1
l niob	0	0	0
u niob	0	0	0
l vana	0	0	0
u vana	0.015	0.015	0.015
l c3	0	0	0
u c3	0.48	0	0

APPENDIX B.2

Tableaux Rule Base for Mechanical Properties for AS3678 Material Standard

	GRADE	THICK	I ysreq	I tsreq	I el
Rule 1	AS3678 200	<=8	200	300	24
Rule 2	AS3678 200	>8 & <=12	200	300	24
Rule 3	AS3678 250	<=8	280	410	22
Rule 4	AS3678 250Z	<=8	280	410	22
Rule 5	AS3678 250	>8 & <=12	260	410	22
Rule 6	AS3678 250Z	>8 & <=12	260	410	22
Rule 7	AS3678 250	>12 & <=20	250	410	22
Rule 8	AS3678 250Z	>12 & <=20	250	410	22
Rule 9	AS3678 250	>20 & <=50	250	410	22
Rule 10	AS3678 250Z	>20 & <=50	250	410	22
Rule 11	AS3678 250	>50 & <=80	240	410	22
Rule 12	AS3678 250Z	>50 & <=80	240	410	22
Rule 13	AS3678 250	>80 & <=150	230	410	22
Rule 14	AS3678 250Z	>80 & <=150	230	410	22
Rule 15	AS3678 250 L15	<=8	280	410	22
Rule 16	AS3678 250 L15	>8 & <=12	260	410	22
Rule 17	AS3678 250 L15	>12 & <=20	250	410	22

	GRADE	THICK	I ysreq	I tsreq	I el
Rule 18	AS3678 250 L15	>20 & <=50	250	410	22
Rule 19	AS3678 250 L15	>50 & <=80	240	410	22
Rule 20	AS3678 250 L15	>80 & <=150	240	410	22
Rule 21	AS3678 300	<=8	320	430	21
Rule 22	AS3678 300	>8 & <=12	310	430	21
Rule 23	AS3678 300	>12 & <=20	300	430	21
Rule 24	AS3678 300	>20 & <=50	280	430	21
Rule 25	AS3678 300	>50 & <=80	280	430	21
Rule 26	AS3678 300	>80 & <=150	280	430	21
Rule 27	AS3678 300 L15	<=8	320	430	21
Rule 28	AS3678 300 L15	>8 & <=12	310	430	21
Rule 29	AS3678 300 L15	>12 & <=20	300	430	21
Rule 30	AS3678 300 L15	>20 & <=50	280	430	21
Rule 31	AS3678 300 L15	>50 & <=80	280	430	21
Rule 32	AS3678 300 L15	>80 & <=150	280	430	21
Rule 33	AS3678 350	<=8	360	450	20
Rule 34	AS3678 350	>8 & <=12	360	450	20

	GRADE	THICK	I ysreq	I tsreq	I el
Rule 35	AS3678 350	>12 & <=20	350	450	20
Rule 36	AS3678 350	>20 & <=50	340	450	20
Rule 37	AS3678 350	>50 & <=80	340	450	20
Rule 38	AS3678 350	>80 & <=150	330	450	20
Rule 39	AS3678 350 L15	<=8	360	450	20
Rule 40	AS3678 350 L15	>8 & <=12	360	450	20
Rule 41	AS3678 350 L15	>12 & <=20	350	450	20
Rule 42	AS3678 350 L15	>20 & <=50	340	450	20
Rule 43	AS3678 350 L15	>50 & <=80	340	450	20
Rule 44	AS3678 350 L15	>80 & <=150	330	450	20
Rule 45	AS3678 400	<=8	400	480	18
Rule 46	AS3678 400	>8 & <=12	400	480	18
Rule 47	AS3678 400	>12 & <=20	380	480	18
Rule 48	AS3678 400	>20 & <=50	360	480	18
Rule 49	AS3678 400 L15	<=8	400	480	18
Rule 50	AS3678 400 L15	>8 & <=12	400	480	18
Rule 51	AS3678 400 L15	>12 & <=20	380	480	18
Rule 52	AS3678 400 L15	>20 & <=50	360	480	18

APPENDIX B.3

Tableaux Rule Base for Charpy Values for AS3678 Material Standard

	GRADE	T SIZE	avg ener	ind ener
Rule 1	AS3678 250 L15	10x10	27	20
Rule 2	AS3678 250 L15	10x7.5	22	16
Rule 3	AS3678 250 L15	10x5	18	13
Rule 4	AS3678 300 L15	10x10	27	20
Rule 5	AS3678 300 L15	10x7.5	22	16
Rule 6	AS3678 300 L15	10x5	18	13
Rule 7	AS3678 350 L15	10x10	27	20
Rule 8	AS3678 350 L15	10x7.5	22	16
Rule 9	AS3678 350 L15	10x5	18	13
Rule 10	AS3678 400 L15	10x10	27	20
Rule 11	AS3678 400 L15	10x7.5	22	16
Rule 12	AS3678 400 L15	10x5	18	13
Rule 13	AS3678 WR350 1L0	10x10	27	20
Rule 14	AS3678 WR350 1L0	10x7.5	22	16
Rule 15	AS3678 WR350 1L0	10x5	18	13

APPENDIX B.4

Tableaux Rule Base for Chemistry Rules for AS3678 Material Standard

	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6	Rule 7	Rule 8	Rule 9	Rule 10
CSRC	111	112	113	114	115	116	117	118	211	212
l carb	0	0	0	0	0	0	0	0	0	0
u carb	0	0	0	0	0	0	0	0	0	0
l sili	0	0	0	0	0	0	0	0	0	0
u sili	0	0	0	0	0	0	0	0	0	0
l mang	0	0	0	0	0	0	0	0	0	0
u mang	0	0	0	0	0	0	0	0	0	0
l phos	0	0	0	0	0	0	0	0	0	0
u phos	0	0	0	0	0	0	0	0	0	0
l sulp	0	0	0	0	0	0	0	0	0	0
u sulp	0.020	0.010	0.005	0.005	0.005	0.008	0.010	0.005	0.010	0.005
l crom	0	0	0	0	0	0	0	0	0	0
u crom	0	0	0	0	0	0	0	0	0	0
l nick	0	0	0	0	0	0	0	0	0	0
u nick	0	0	0	0	0	0	0	0	0	0
l copp	0	0	0	0	0	0	0	0	0	0
u copp	0	0	0	0	0	0	0	0	0	0
l alum	0	0	0	0	0	0	0	0	0	0
u alum	0	0	0	0	0	0	0	0	0	0
l tita	0	0	0	0	0	0	0	0	0	0
u tita	0	0	0	0	0	0	0	0	0	0
l moli	0	0	0	0	0	0	0	0	0	0
u moli	0	0	0	0	0	0	0	0	0	0
l niob	0	0	0	0	0	0	0	0	0	0
u niob	0	0	0	0	0	0	0	0	0	0
l vana	0	0	0	0	0	0	0	0	0	0
u vana	0	0	0	0	0	0	0	0	0	0
l c3	0	0	0	0	0	0	0	0	0	0
u c3	0	0	0	0	0	0	0	0	0	0
l tsreq	0	0	0	0	0	0	0	0	0	0
u tsreq	0	0	0	0	0	0	0	0	0	0
l ysreq	0	0	0	0	0	0	0	0	0	0
u ysreq	0	0	0	0	0	0	0	0	0	0
u hydr	2.6	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9

	Rule 11	Rule 12	Rule 13	Rule 14	Rule 15	Rule 16	Rule 17	Rule 18	Rule 19	Rule 20
CSRC	c51	c52	c53	c54	c55	c56	c57	c58	c59	c50
l carb	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.11	0.12
u carb	0	0	0	0	0	0	0	0	0	0
l sili	0	0	0	0	0	0	0	0	0	0
u sili	0	0	0	0	0	0	0	0	0	0
l mang	0	0	0	0	0	0	0	0	0	0
u mang	0	0	0	0	0	0	0	0	0	0
l phos	0	0	0	0	0	0	0	0	0	0
u phos	0	0	0	0	0	0	0	0	0	0
l sulp	0	0	0	0	0	0	0	0	0	0
u sulp	0	0	0	0	0	0	0	0	0	0
l crom	0	0	0	0	0	0	0	0	0	0
u crom	0	0	0	0	0	0	0	0	0	0
l nick	0	0	0	0	0	0	0	0	0	0
u nick	0	0	0	0	0	0	0	0	0	0
l copp	0	0	0	0	0	0	0	0	0	0
u copp	0	0	0	0	0	0	0	0	0	0
l alum	0	0	0	0	0	0	0	0	0	0
u alum	0	0	0	0	0	0	0	0	0	0
l tita	0	0	0	0	0	0	0	0	0	0
u tita	0	0	0	0	0	0	0	0	0	0
l moli	0	0	0	0	0	0	0	0	0	0
u moli	0	0	0	0	0	0	0	0	0	0
l niob	0	0	0	0	0	0	0	0	0	0
u niob	0	0	0	0	0	0	0	0	0	0
l vana	0	0	0	0	0	0	0	0	0	0
u vana	0	0	0	0	0	0	0	0	0	0
l c3	0	0	0	0	0	0	0	0	0	0
u c3	0	0	0	0	0	0	0	0	0	0
l tsreq	0	0	0	0	0	0	0	0	0	0
u tsreq	0	0	0	0	0	0	0	0	0	0
l ysreq	0	0	0	0	0	0	0	0	0	0
u ysreq	0	0	0	0	0	0	0	0	0	0
u hydr	0	0	0	0	0	0	0	0	0	0

APPENDIX C

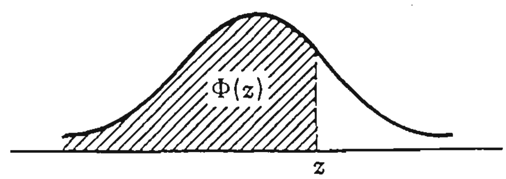
NORMAL TABLES

APPENDIX C

Normal Tables

Cumulative Normal Distribution[a]

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-u^2/2}\, du$$



z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.50000	0.50399	0.50798	0.51197	0.51595	0.51994	0.52392	0.52790	0.53188	0.53586
0.1	0.53983	0.54380	0.54776	0.55172	0.55567	0.55962	0.56356	0.56749	0.57142	0.57535
0.2	0.57926	0.58317	0.58706	0.59095	0.59483	0.59871	0.60257	0.60642	0.61026	0.61409
0.3	0.61791	0.62172	0.62552	0.62930	0.63307	0.63683	0.64058	0.64431	0.64803	0.65173
0.4	0.65542	0.65910	0.66276	0.66640	0.67003	0.67364	0.67724	0.68082	0.68439	0.68793
0.5	0.69146	0.69497	0.69847	0.70194	0.70540	0.70884	0.71226	0.71566	0.71904	0.72240
0.6	0.72575	0.72907	0.73237	0.73565	0.73891	0.74215	0.74537	0.74857	0.75175	0.75490
0.7	0.75804	0.76115	0.76424	0.76730	0.77035	0.77337	0.77637	0.77935	0.78230	0.78524
0.8	0.78814	0.79103	0.79389	0.79673	0.79955	0.80234	0.80511	0.80785	0.81057	0.81327
0.9	0.81594	0.81859	0.82121	0.82381	0.82639	0.82894	0.83147	0.83398	0.83646	0.83891
1.0	0.84134	0.84375	0.84614	0.84850	0.85083	0.85314	0.85543	0.85769	0.85993	0.86214
1.1	0.86433	0.86650	0.86864	0.87076	0.87286	0.87493	0.87698	0.87900	0.88100	0.88298
1.2	0.88493	0.88686	0.88877	0.89065	0.89251	0.89435	0.89617	0.89796	0.89973	0.90147
1.3	0.90320	0.90490	0.90658	0.90824	0.90988	0.91149	0.91309	0.91466	0.91621	0.91774
1.4	0.91924	0.92073	0.92220	0.92364	0.92507	0.92647	0.92786	0.92922	0.93056	0.93189
1.5	0.93319	0.93448	0.93574	0.93699	0.93822	0.93943	0.94062	0.94179	0.94295	0.94408
1.6	0.94520	0.94630	0.94738	0.94845	0.94950	0.95053	0.95154	0.95254	0.95352	0.95449
1.7	0.95543	0.95637	0.95728	0.95818	0.95907	0.95994	0.96080	0.96164	0.96246	0.96327
1.8	0.96407	0.96485	0.96562	0.96638	0.96712	0.96784	0.96856	0.96926	0.96995	0.97062
1.9	0.97128	0.97193	0.97257	0.97320	0.97381	0.97441	0.97500	0.97558	0.97615	0.97670
2.0	0.97725	0.97778	0.97831	0.97882	0.97932	0.97982	0.98030	0.98077	0.98124	0.98169
2.1	0.98214	0.98257	0.98300	0.98341	0.98382	0.98422	0.98461	0.98500	0.98537	0.98574
2.2	0.98610	0.98645	0.98679	0.98713	0.98745	0.98778	0.98809	0.98840	0.98870	0.98899
2.3	0.98928	0.98956	0.98983	0.99010	0.99036	0.99061	0.99086	0.99111	0.99134	0.99158
2.4	0.99180	0.99202	0.99224	0.99245	0.99266	0.99286	0.99305	0.99324	0.99343	0.99361
2.5	0.99379	0.99396	0.99413	0.99430	0.99446	0.99461	0.99477	0.99492	0.99506	0.99520
2.6	0.99534	0.99547	0.99560	0.99573	0.99585	0.99598	0.99609	0.99621	0.99632	0.99643
2.7	0.99653	0.99664	0.99674	0.99683	0.99693	0.99702	0.99711	0.99720	0.99728	0.99736
2.8	0.99744	0.99752	0.99760	0.99767	0.99774	0.99781	0.99788	0.99795	0.99801	0.99807
2.9	0.99813	0.99819	0.99825	0.99831	0.99836	0.99841	0.99846	0.99851	0.99856	0.99861
3.0	0.99865	0.99869	0.99874	0.99878	0.99882	0.99886	0.99889	0.99893	0.99897	0.99900
3.1	0.99903	0.99906	0.99910	0.99913	0.99916	0.99918	0.99921	0.99924	0.99926	0.99929
3.2	0.99931	0.99934	0.99936	0.99938	0.99940	0.99942	0.99944	0.99946	0.99948	0.99950
3.3	0.99952	0.99953	0.99957	0.99957	0.99958	0.99960	0.99961	0.99962	0.99964	0.99965
3.4	0.99966	0.99968	0.99969	0.99970	0.99971	0.99972	0.99973	0.99974	0.99975	0.99976
3.5	0.99977	0.99978	0.99978	0.99979	0.99980	0.99981	0.99981	0.99982	0.99983	0.99983
3.6	0.99984	0.99985	0.99985	0.99986	0.99986	0.99987	0.99987	0.99988	0.99988	0.99989
3.7	0.99989	0.99990	0.99990	0.99990	0.99991	0.99991	0.99992	0.99992	0.99992	0.99992
3.8	0.99993	0.99993	0.99993	0.99994	0.99994	0.99994	0.99994	0.99995	0.99995	0.99995
3.9	0.99995	0.99995	0.99996	0.99996	0.99996	0.99996	0.99996	0.99996	0.99997	0.99997

[a] Reproduced with permission from Pearson and Hartley, *Biometrika Tables for Statisticians*, Vol. 1 (1958), pp. 104–108.

APPENDIX D

SAMPLE INPUTS/OUTPUTS

APPENDIX D.1

Input/Output for AS3678-250 Grade and Thickness 10.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
1	AS3678_250	1200 10.00 10.00	100	5000.00	Structural

Special Requirement Codes: zzz

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	0.000						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	0.5000	0.1000	0.0020	0.0000
Max SAC Values	0.1600	1.0000	0.2000	0.0390	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250 AND THICKNESS 10.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	446	260	330	0.3100	0.1400	0.7500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	450	260	333	0.3183	0.1400	0.8000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	453	260	336	0.3267	0.1400	0.8500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	449	260	335	0.3100	0.1400	0.7000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	452	260	337	0.3183	0.1400	0.7500	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	455	260	340	0.3267	0.1400	0.8000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	451	260	339	0.3100	0.1400	0.6500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	455	260	342	0.3183	0.1400	0.7000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	446	260	327	0.3033	0.1500	0.6500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	449	260	330	0.3117	0.1500	0.7000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	452	260	333	0.3200	0.1500	0.7500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	455	260	335	0.3283	0.1500	0.8000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	448	260	332	0.3033	0.1500	0.6000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	452	260	334	0.3117	0.1500	0.6500	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	455	260	337	0.3200	0.1500	0.7000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	451	260	336	0.3033	0.1500	0.5500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
410	454	260	339	0.3117	0.1500	0.6000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000

SAC RECOMMENDED FOR GRADE AS3678_250 AND THICKNESS 10.00 mm

SGN is X33A9 AND SAC Number is 0625

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1500	0.6500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000

APPENDIX D.2

Input/Output for AS3678-250-L15 Grade and Thickness 20.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
2	AS3678_250_L15	1200 20.00 11.00	100	4000.00	Structural

Special Requirement Codes: 114 zzz

Explanation for the Special Requirement Code 114:

Longitudinal Charpys. Temperature < -15 (-20 or -30)Deg Celsius
Minimum Absorbed Energy - Average of 3 Tests >27J & <=48J
and Individual >20J & <= 40J

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.005	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	1.900						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	0.5000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.0000	0.3000	0.0040	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250_L15 AND THICKNESS 20.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	451	250	319	0.3433	0.1400	0.8500	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	322	0.3517	0.1400	0.9000	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	458	250	325	0.3600	0.1400	0.9500	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	451	250	321	0.3350	0.1400	0.7500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	323	0.3433	0.1400	0.8000	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	457	250	326	0.3517	0.1400	0.8500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	460	250	329	0.3600	0.1400	0.9000	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	332	0.3683	0.1400	0.9500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	453	250	325	0.3350	0.1400	0.7000	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	328	0.3433	0.1400	0.7500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	331	0.3517	0.1400	0.8000	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	333	0.3600	0.1400	0.8500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	466	250	336	0.3683	0.1400	0.9000	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	469	250	339	0.3767	0.1400	0.9500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	451	250	316	0.3367	0.1500	0.7500	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	319	0.3450	0.1500	0.8000	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	457	250	321	0.3533	0.1500	0.8500	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	460	250	324	0.3617	0.1500	0.9000	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	327	0.3700	0.1500	0.9500	0.2000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	453	250	320	0.3367	0.1500	0.7000	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	323	0.3450	0.1500	0.7500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	326	0.3533	0.1500	0.8000	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	329	0.3617	0.1500	0.8500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	466	250	331	0.3700	0.1500	0.9000	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	469	250	334	0.3783	0.1500	0.9500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	325	0.3367	0.1500	0.6500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	328	0.3450	0.1500	0.7000	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	462	250	330	0.3533	0.1500	0.7500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	465	250	333	0.3617	0.1500	0.8000	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	468	250	336	0.3700	0.1500	0.8500	0.3000	0.0040	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

SACS RECOMMENDED FOR GRADE AS3678_250_L15 AND THICKNESS 20.00 mm

SGN is X34A9 AND SAC Number is 0361

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1400	0.9000	0.2000	0.0040	0.0170	0.0230	0.0140	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

SGN is X34A9 AND SAC Number is 0564

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1500	0.7500	0.2500	0.0040	0.0170	0.0230	0.0140	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

APPENDIX D.3

Input/Output for AS3678-250 Grade and Thickness 20.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
3	AS3678_250	900 20.00 11.00	150	5000.00	Structural

Special Requirement Codes: zzz

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	0.000						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	0.5000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.0000	0.3000	0.0390	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250 AND THICKNESS 20.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	451	250	319	0.3433	0.1400	0.8500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	322	0.3517	0.1400	0.9000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	458	250	325	0.3600	0.1400	0.9500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	451	250	321	0.3350	0.1400	0.7500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	323	0.3433	0.1400	0.8000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	457	250	326	0.3517	0.1400	0.8500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	460	250	329	0.3600	0.1400	0.9000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	332	0.3683	0.1400	0.9500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	453	250	325	0.3350	0.1400	0.7000	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	328	0.3433	0.1400	0.7500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	331	0.3517	0.1400	0.8000	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	333	0.3600	0.1400	0.8500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	466	250	336	0.3683	0.1400	0.9000	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	469	250	339	0.3767	0.1400	0.9500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	451	250	316	0.3367	0.1500	0.7500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	454	250	319	0.3450	0.1500	0.8000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	457	250	321	0.3533	0.1500	0.8500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	460	250	324	0.3617	0.1500	0.9000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	327	0.3700	0.1500	0.9500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	453	250	320	0.3367	0.1500	0.7000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	323	0.3450	0.1500	0.7500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	326	0.3533	0.1500	0.8000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	463	250	329	0.3617	0.1500	0.8500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	466	250	331	0.3700	0.1500	0.9000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	469	250	334	0.3783	0.1500	0.9500	0.2500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	456	250	325	0.3367	0.1500	0.6500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	459	250	328	0.3450	0.1500	0.7000	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	462	250	330	0.3533	0.1500	0.7500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	465	250	333	0.3617	0.1500	0.8000	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000
410	468	250	336	0.3700	0.1500	0.8500	0.3000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

SACS RECOMMENDED FOR GRADE AS3678_250 AND THICKNESS 20.00 mm

SGN is X34A9 AND SAC Number is 0361

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1400	0.9000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

SGN is X34A9 AND SAC Number is 0638

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1500	0.8000	0.2500	0.0390	0.0170	0.0230	0.0140	0.0100	0.0300	0.0000	0.0000	0.0000	0.0045	0.0000

APPENDIX D.4

Input/Output for AS3678-250-L15 Grade and Thickness 40.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
4	AS3678_250_L15	1000 40.00 10.00	100	5000.00	Structural

Special Requirement Codes: 114 zzz

Explanation for the Special Requirement Code 114:

Longitudinal Charpys. Temperature < -15 (-20 or -30)Deg Celsius
Minimum Absorbed Energy - Average of 3 Tests >27J & <=48J
and Individual >20J & <= 40J

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.005	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen					
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	1.900						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	1.0000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.3000	0.3000	0.0040	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250_L15 AND THICKNESS 40.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	438	250	289	0.3700	0.1400	1.0000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	442	250	292	0.3783	0.1400	1.0500	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	445	250	295	0.3867	0.1400	1.1000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	448	250	297	0.3950	0.1400	1.1500	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	451	250	300	0.4033	0.1400	1.2000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	303	0.4117	0.1400	1.2500	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	444	250	296	0.3783	0.1400	1.0000	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	447	250	299	0.3867	0.1400	1.0500	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	302	0.3950	0.1400	1.1000	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	304	0.4033	0.1400	1.1500	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	303	0.3867	0.1400	1.0000	0.3000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	453	250	306	0.3950	0.1400	1.0500	0.3000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	444	250	291	0.3800	0.1500	1.0000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	447	250	294	0.3883	0.1500	1.0500	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	451	250	297	0.3967	0.1500	1.1000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	300	0.4050	0.1500	1.1500	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	299	0.3883	0.1500	1.0000	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	453	250	301	0.3967	0.1500	1.0500	0.2500	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	294	0.3900	0.1600	1.0000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000

SAC RECOMMENDED FOR GRADE AS3678_250_L15 AND THICKNESS 40.00 mm

SGN is X35A9 AND SAC Number is 0310

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1400	1.1000	0.2000	0.0040	0.0180	0.0230	0.0160	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000

APPENDIX D.5

Input/Output for AS3678-250 Grade and Thickness 40.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
5	AS3678_250	900 40.00 7.00	150	4000.00	Structural

Special Requirement Codes: zzz

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	0.000						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	1.0000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.3000	0.3000	0.0390	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250 AND THICKNESS 40.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	438	250	289	0.3700	0.1400	1.0000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	442	250	292	0.3783	0.1400	1.0500	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	445	250	295	0.3867	0.1400	1.1000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	448	250	297	0.3950	0.1400	1.1500	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	451	250	300	0.4033	0.1400	1.2000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	303	0.4117	0.1400	1.2500	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	444	250	296	0.3783	0.1400	1.0000	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	447	250	299	0.3867	0.1400	1.0500	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	302	0.3950	0.1400	1.1000	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	304	0.4033	0.1400	1.1500	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	303	0.3867	0.1400	1.0000	0.3000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	453	250	306	0.3950	0.1400	1.0500	0.3000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	444	250	291	0.3800	0.1500	1.0000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	447	250	294	0.3883	0.1500	1.0500	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	451	250	297	0.3967	0.1500	1.1000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	454	250	300	0.4050	0.1500	1.1500	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	299	0.3883	0.1500	1.0000	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	453	250	301	0.3967	0.1500	1.0500	0.2500	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000
410	450	250	294	0.3900	0.1600	1.0000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000

SAC RECOMMENDED FOR GRADE AS3678_250 AND THICKNESS 40.00 mm

SGN is X35A9 AND SAC Number is 0310

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1400	1.1000	0.2000	0.0390	0.0180	0.0230	0.0160	0.0100	0.0250	0.0000	0.0180	0.0000	0.0059	0.0000

APPENDIX D.6

Input/Output for AS3678-250-L15 Grade and Thickness 80.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
6	AS3678_250_L15	1000 80.00 10.00	100	5000.00	Structural

Special Requirement Codes: 114 zzz

Explanation for the Special Requirement Code 114:

Longitudinal Charpys. Temperature < -15 (-20 or -30)Deg Celsius
Minimum Absorbed Energy - Average of 3 Tests >27J & <=48J
and Individual >20J & <= 40J

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.005	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	1.900						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	1.0000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.3000	0.3000	0.0040	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250_L15 AND THICKNESS 80.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	462	240	281	0.4217	0.1400	1.2500	0.2500	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	465	240	283	0.4300	0.1400	1.3000	0.2500	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	461	240	282	0.4133	0.1400	1.1500	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	285	0.4217	0.1400	1.2000	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	288	0.4300	0.1400	1.2500	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	462	240	276	0.4233	0.1500	1.2500	0.2000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	465	240	279	0.4317	0.1500	1.3000	0.2000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	461	240	277	0.4150	0.1500	1.1500	0.2500	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	280	0.4233	0.1500	1.2000	0.2500	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	283	0.4317	0.1500	1.2500	0.2500	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	460	240	279	0.4067	0.1500	1.0500	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	282	0.4150	0.1500	1.1000	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	285	0.4233	0.1500	1.1500	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	470	240	287	0.4317	0.1500	1.2000	0.3000	0.0040	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000

SAC RECOMMENDED FOR GRADE AS3678_250_L15 AND THICKNESS 80.00 mm

SGN is X36A9 AND SAC Number is 0322

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1500	1.2000	0.3000	0.0040	0.0190	0.0230	0.0170	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000

APPENDIX D.7

Input/Output for AS3678-250 Grade and Thickness 80.00 mm

Details of the order/enquiry:

Item No.	Standard Number	Size W(mm)xT(mm)xL(m)	Qty	Weight (Tons)	End Use
7	AS3678_250	1100 80.00 8.00	200	6000.00	Structural

Special Requirement Codes: zzz

Certification Limit (CLIM):

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		R2							
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.015	0.000	0.450								

Modified Chemistry Limits:

Carbon		Manganese		Silicon		Sulphur		Phosphorus		Chromium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.220	0.000	1.700	0.000	0.550	0.000	0.040	0.000	0.040	0.000	0.300

Nickel		Copper		Aluminium		Titanium		Molybdenum		Niobium	
min	max	min	max	min	max	min	max	min	max	min	max
0.000	0.500	0.000	0.400	0.000	0.100	0.000	0.040	0.000	0.100	0.000	0.000

Vanadium		CEQ3		Hydrogen						
min	max	min	max	(ppm)	min	max	min	max	min	max
0.000	0.015	0.000	0.450	0.000						

Range of SAC Values:

	Carbon	Manganese	Silicon	Sulphur	Phosphorus
Min SAC Values	0.1400	1.0000	0.2000	0.0020	0.0000
Max SAC Values	0.1600	1.3000	0.3000	0.0390	0.0350

	Nickel	Chromium	Molybdenum	Copper	Aluminium
Min SAC Values	0.0500	0.0200	0.0050	0.0500	0.0050
Max SAC Values	0.4950	0.2800	0.0950	0.3800	0.0980

	Nitrogen	Titanium	Niobium	Vanadium	Boron
Min SAC Values	0.0020	0.0000	0.0050	0.0050	0.0003
Max SAC Values	0.0150	0.0350	0.0100	0.0100	0.0050

COMPUTED SAC VALUES FOR GRADE AS3678_250 AND THICKNESS 80.00 mm

RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
410	462	240	281	0.4217	0.1400	1.2500	0.2500	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	465	240	283	0.4300	0.1400	1.3000	0.2500	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	461	240	282	0.4133	0.1400	1.1500	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	285	0.4217	0.1400	1.2000	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	288	0.4300	0.1400	1.2500	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	462	240	276	0.4233	0.1500	1.2500	0.2000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	465	240	279	0.4317	0.1500	1.3000	0.2000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	461	240	277	0.4150	0.1500	1.1500	0.2500	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	280	0.4233	0.1500	1.2000	0.2500	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	283	0.4317	0.1500	1.2500	0.2500	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	460	240	279	0.4067	0.1500	1.0500	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	464	240	282	0.4150	0.1500	1.1000	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	467	240	285	0.4233	0.1500	1.1500	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000
410	470	240	287	0.4317	0.1500	1.2000	0.3000	0.0390	0.0190	0.0230	0.0170	0.0000	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000

SAC RECOMMENDED FOR GRADE AS3678_250 AND THICKNESS 80.00 mm

SGN is X36A9 AND SAC Number is 0322

C	Mn	Si	S	P	Ni	Cr	Cu	Al	N	Ti	Nb	V	B
0.1500	1.2000	0.3000	0.0390	0.0190	0.0230	0.0170	0.0100	0.0250	0.0000	0.0180	0.0000	0.0065	0.0000

APPENDIX E

RANKED STEELMAKING AIM CHEMISTRY LIST

APPENDIX E

Ranked Steelmaking Aim Chemistry List for AS3678-250 Grade and Thickness 10.00 mm

WSMF	RTS	CTS	RYS	CYS	CEQ1	C	Mn	Si	S	P	Ni	Cr	Mo	Cu	Al	N	Ti	Nb	V	B
0.607943	410	455	260	340	0.3267	0.1400	0.8000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.595355	410	452	260	337	0.3183	0.1400	0.7500	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.562424	410	455	260	337	0.3200	0.1500	0.7000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.546424	410	455	260	342	0.3183	0.1400	0.7000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.541035	410	449	260	335	0.3100	0.1400	0.7000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.498526	410	455	260	335	0.3283	0.1500	0.8000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.491265	410	453	260	336	0.3267	0.1400	0.8500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.485938	410	452	260	333	0.3200	0.1500	0.7500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.480159	410	452	260	334	0.3117	0.1500	0.6500	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.479877	410	450	260	333	0.3183	0.1400	0.8000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.475137	410	449	260	330	0.3117	0.1500	0.7000	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.468000	410	446	260	330	0.3100	0.1400	0.7500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.461033	410	451	260	339	0.3100	0.1400	0.6500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.454222	410	446	260	327	0.3033	0.1500	0.6500	0.1000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.423971	410	454	260	339	0.3117	0.1500	0.6000	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.419757	410	448	260	332	0.3033	0.1500	0.6000	0.1500	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000
0.390235	410	451	260	336	0.3033	0.1500	0.5500	0.2000	0.0390	0.0170	0.0230	0.0140	0.0000	0.0100	0.0300	0.0000	0.0000	0.0000	0.0040	0.0000

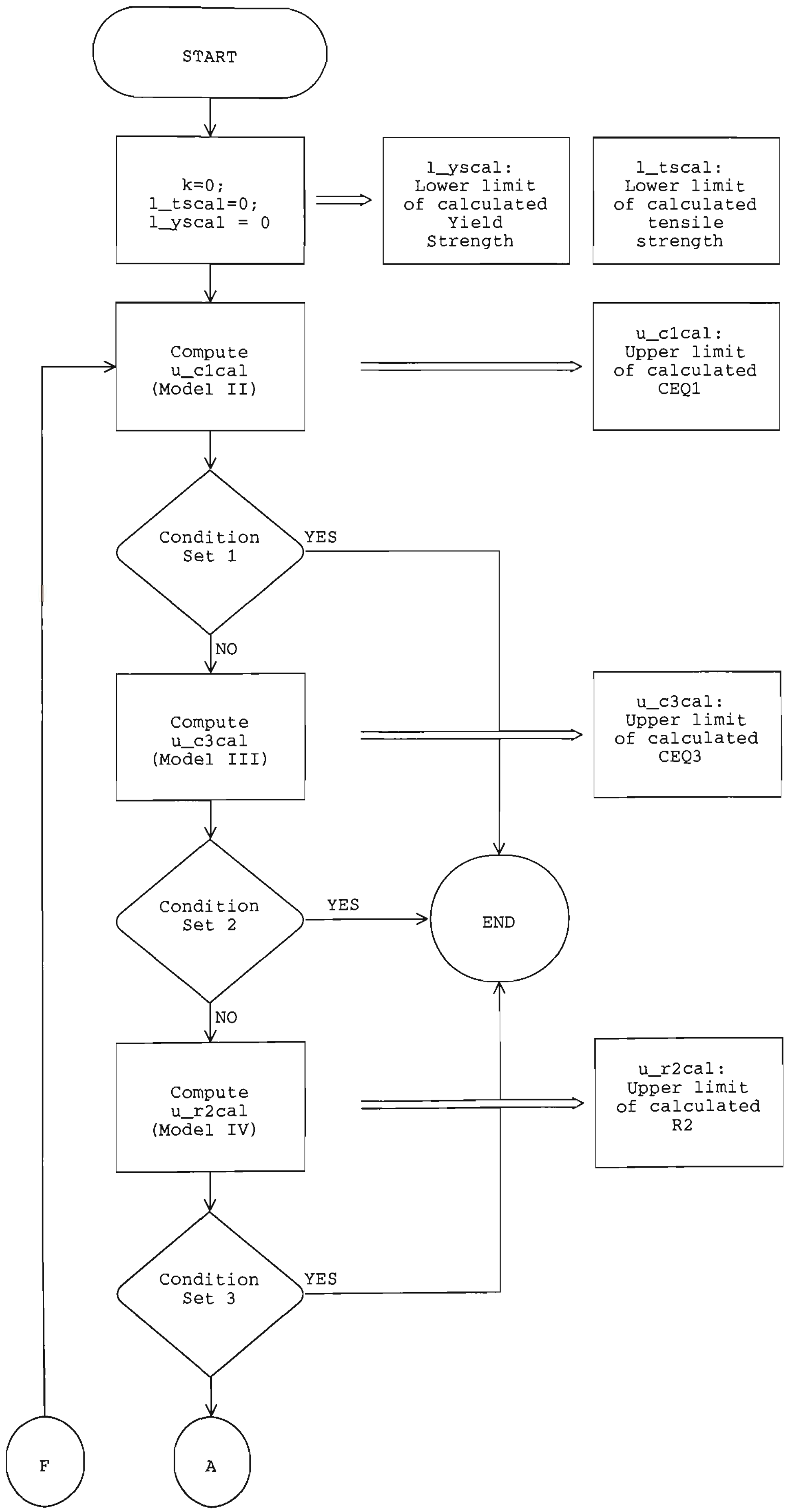
Note: This computation of the Weighted Sum Membership Functions is based on the values of $\beta_1 = 0.40$, $\beta_2 = 0.30$, $\beta_3 = 0.18$ and $\beta_4 = 0.12$.

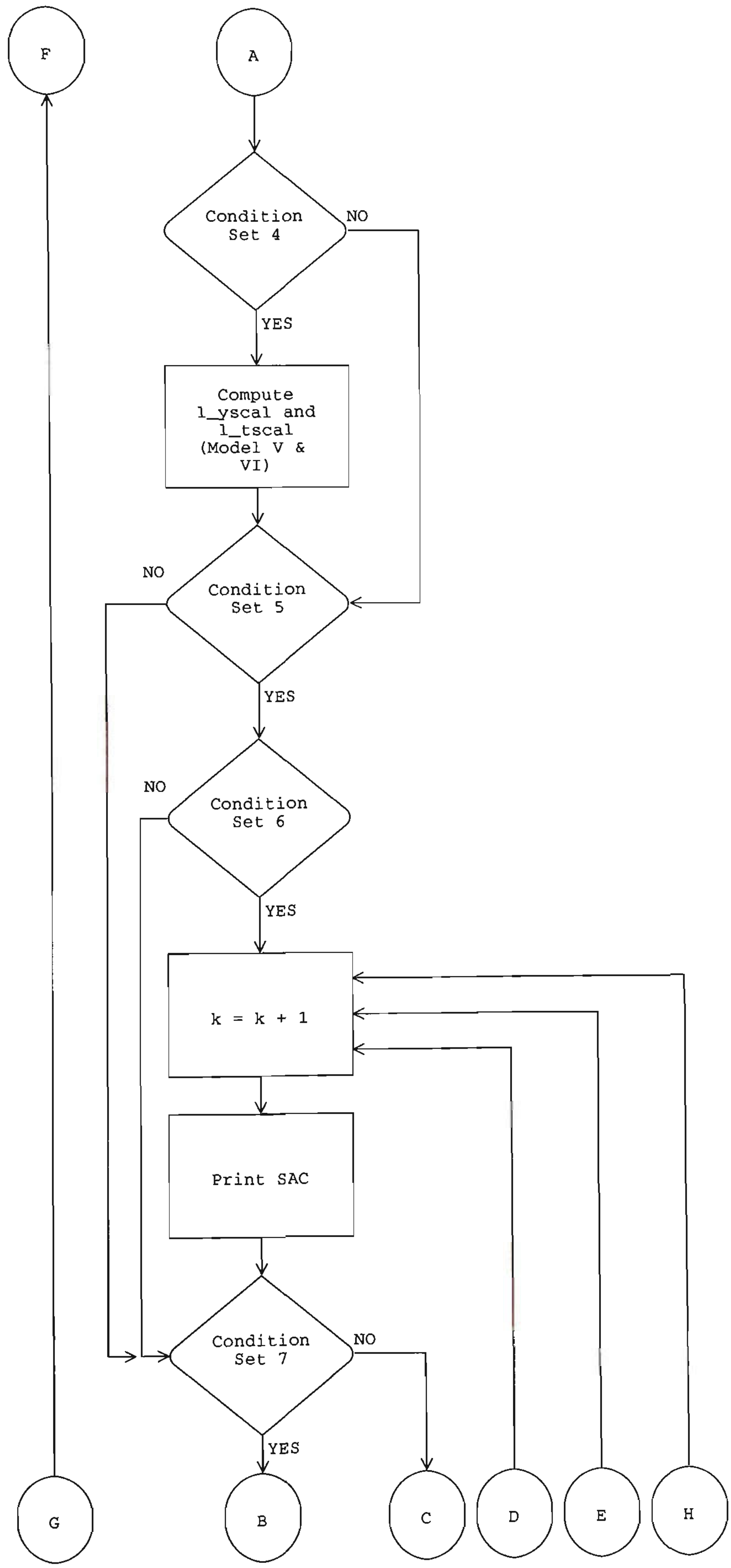
APPENDIX F

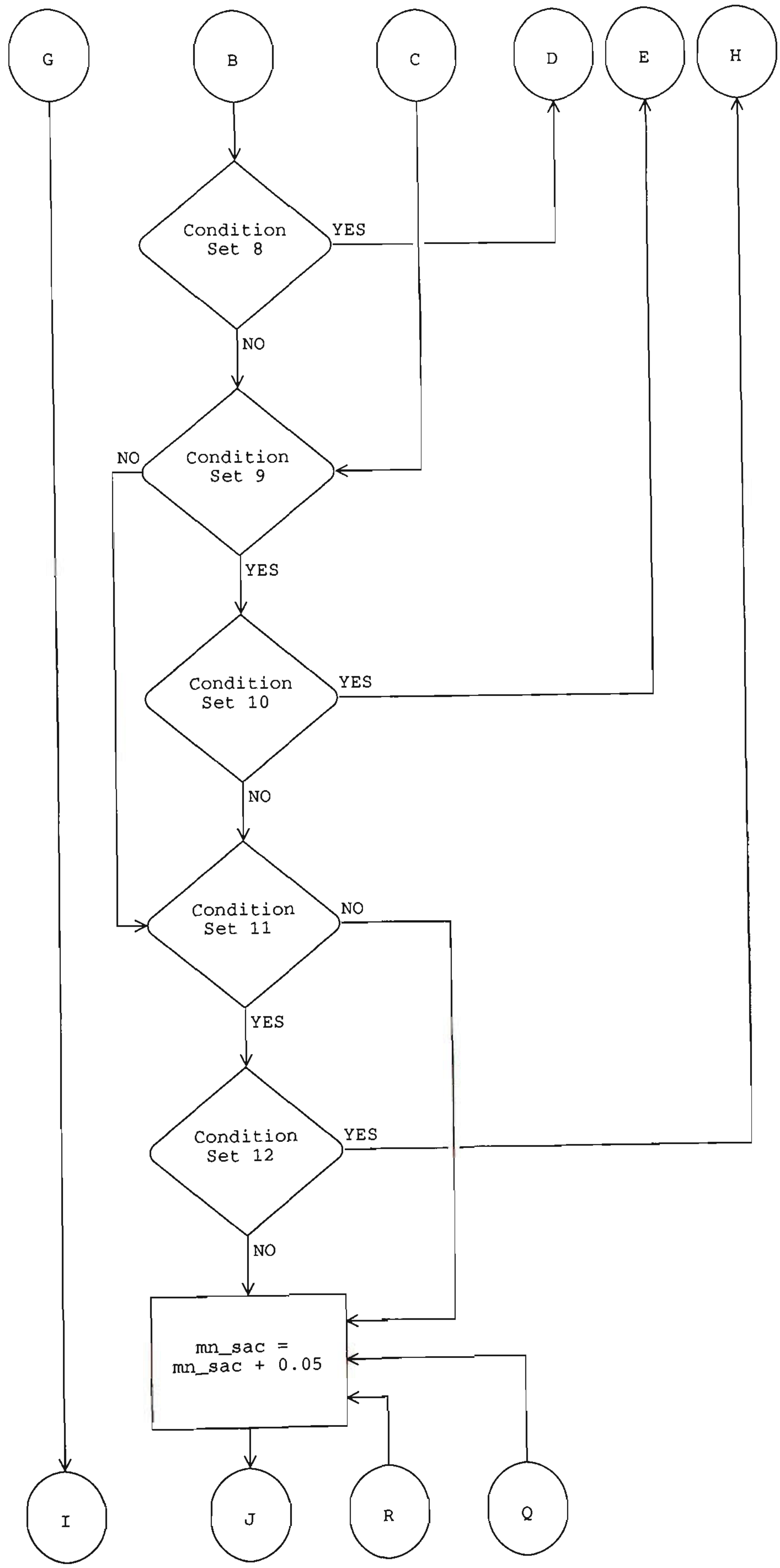
FLOW CHARTS FOR ITERATIVE STRATEGY

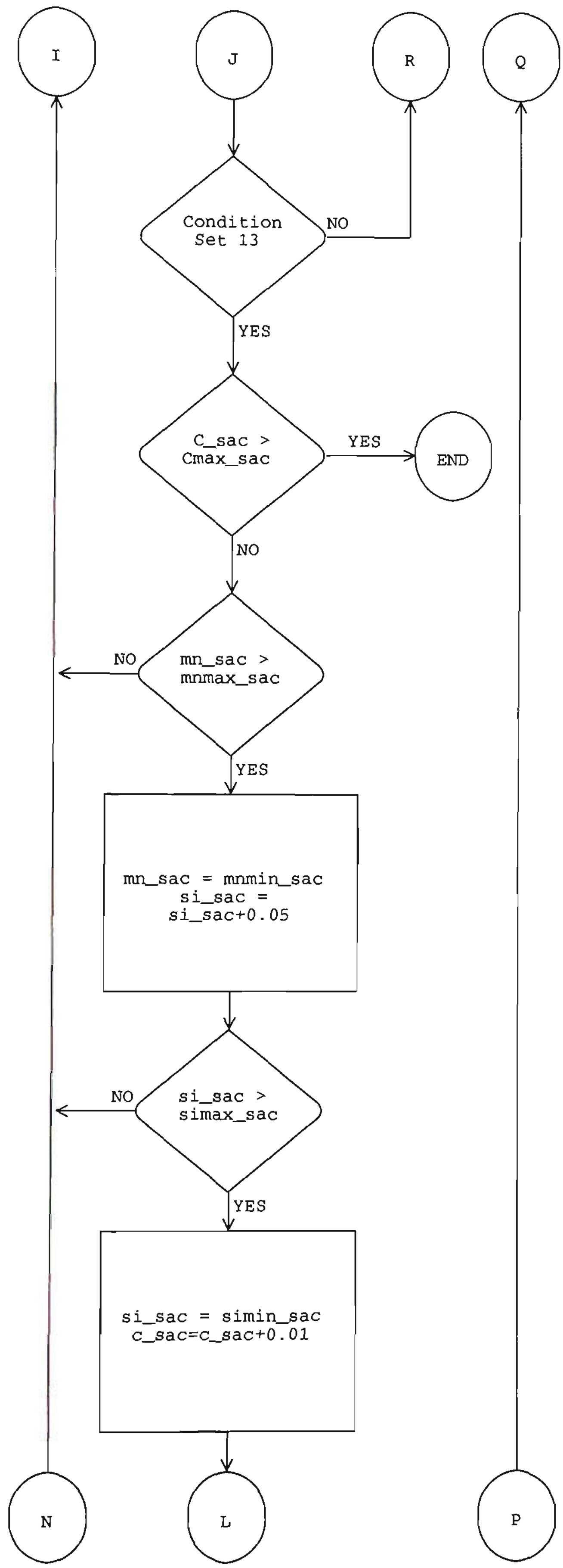
APPENDIX F

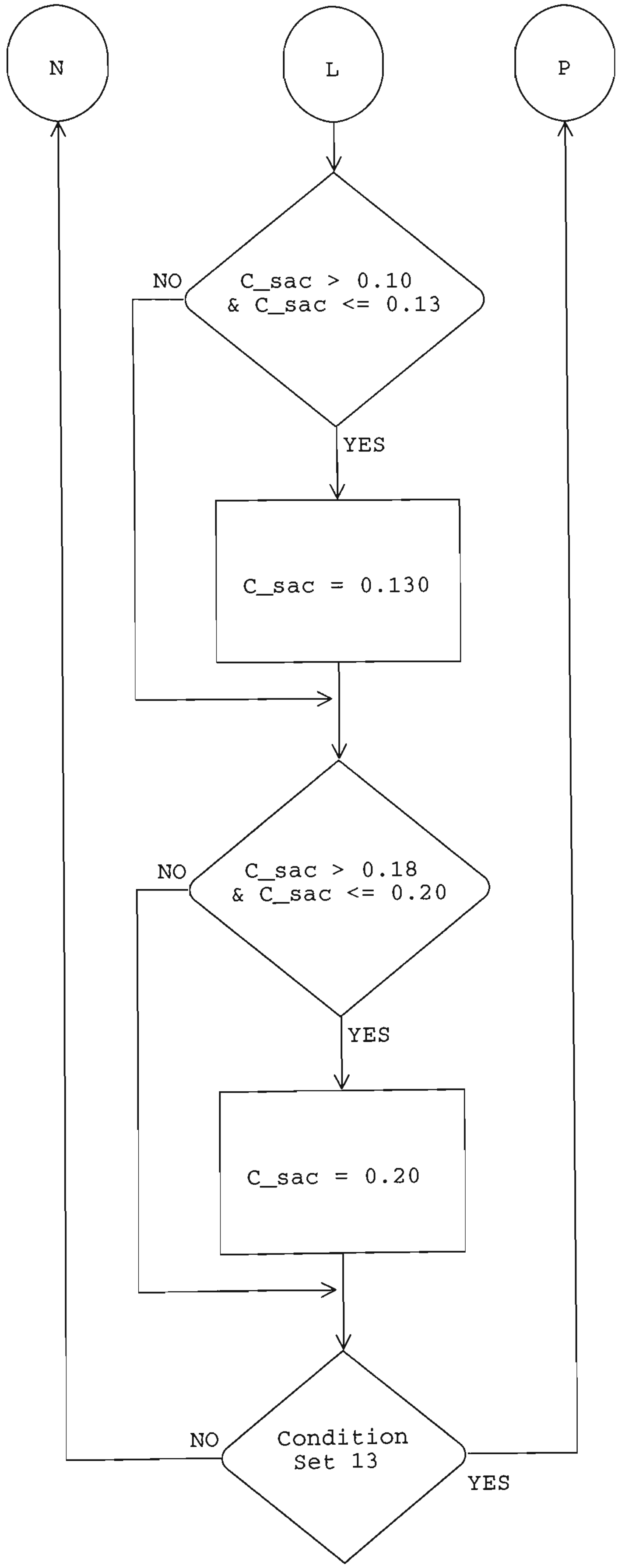
Flow Chart for the Iterative Strategy Utilising Knowledge-Bases




F
A
Condition Set 4
NO
YES
Compute l_yscal and l_tscal (Model V & VI)
NO
Condition Set 5
YES
NO
Condition Set 6
YES
k = k + 1
Print SAC
Condition Set 7
NO
YES
G
B
C
D
E
H


G
B
C
D
E
H
Condition Set 8
YES
NO
Condition Set 9
NO
YES
Condition Set 10
YES
NO
Condition Set 11
NO
YES
Condition Set 12
YES
NO
mn_sac = mn_sac + 0.05
I
J
R
Q


I
J
R
Q
Condition Set 13
NO
YES
C_sac > Cmax_sac
YES
END
NO
NO
mn_sac > mnmax_sac
YES
mn_sac = mnmin_sac
si_sac = si_sac+0.05
NO
si_sac > simax_sac
YES
si_sac = simin_sac
c_sac=c_sac+0.01
N
L
P



N
L
P
C_sac > 0.10
& C_sac <= 0.13
NO
YES
C_sac = 0.130
C_sac > 0.18
& C_sac <= 0.20
NO
YES
C_sac = 0.20
Condition
Set 13
NO
YES

Explanation for the terms used in the Flow Chart for Iterative Process

Condition Set 1: u_c1cal > u_c1 and
c_sac > cmax_sac and
mn_sac > mnmax_sac and
si_sac > simax_sac

Condition Set 2: u_c3cal > u_c3 and
c_sac > cmax_sac and
mn_sac > mnmax_sac and
si_sac > simax_sac

Condition Set 3: u_r2cal > 1 and
c > cmax_sac and
mn_sac > mnmax_sac and
si_sac > simax_sac

Condition Set 4: u_c1cal <= u_c1 and
u_c1cal > l_c1 and
u_c3cal <= (u_c3 - 0.04) and
u_r2cal <= 1

Condition Set 5: thick > 8.0 and thick <= 15.95 and
Grade is AS3678-250 or AS3678-250Z or AS3678-250-L15

Condition Set 6: l_yscal >= (l_ysreq + 20) and
l_tscal >= (l_tsreq + 25) and
u_c1cal <= u_c1 and
u_c1cal <= l_c1 and

u_c3cal <= (u_c3-0.04) and

u_r2cal <= 1 and

l_tscal <= (l_tsreq + 45)

l_tsreq here refers to the lower limit of the required tensile strength and u_c3 refers to the upper limit of CEQ3.

Condition Set 7: thick > 16 and thick <= 31.95 and

Grade is AS3678-250 or AS3678-250Z or AS3678-250-L15

Condition Set 8: l_yscal >= (l_ysreq + 20) and

l_tscal >= (l_tsreq + 40) and

u_c1cal <= u_c1 and

u_c1cal <= l_c1 and

u_c3cal <= (u_c3-0.04) and

u_r2cal <= 1 and

l_tscal <= (l_tsreq + 60)

Condition Set 9: thick > 32 and thick <= 50.95 and

Grade is AS3678-250 or AS3678-250Z or AS3678-250-L15

Condition Set 10: l_yscal >= (l_ysreq + 20) and

l_tscal >= (l_tsreq + 25) and

u_c1cal <= u_c1 and

u_c1cal <= l_c1 and

u_c3cal <= (u_c3-0.04) and

u_r2cal <= 1 and

l_tscal <= (l_tsreq + 45)

Condition Set 11: thick > 50 and thick <= 115 and
Grade is AS3678-250 or AS3678-250Z or AS3678-250-L15

Condition Set 12: l_yscal >= (l_ysreq + 20) and
l_tscal >= (l_tsreq + 50) and
u_c1cal <= u_c1 and
u_c1cal <= l_c1 and
u_c3cal <= (u_c3-0.04) and
u_r2cal <= 1 and
l_tscal <= (l_tsreq + 70)

Condition Set 13: (mn_sac/c_sac) > 3

Model I: $CEQ1_{min}$ = {(l_tsreq + 40) + 0.13 x frt + 0.54 x thick - 396.7} / 519.92
$CEQ1_{max}$ = {(l_tsreq + 67) + 0.13 x frt + 0.54 x thick - 396.7} / 519.92
where l_tsreq is the minimum tensile strength required

Model II: u_c1cal = c_sac + (mn_sac + p_sac x 10 + si_sac)/6

Model III: u_c3cal = c_sac + mn_sac/6 + (cr_sac + mo_sac + v_sac) x 5 + (cu_sac + ni_sac)/15

Model IV: u_r2cal = ni_sac + cr_sac + cu_sac + mo_sac

Model V: l_yscal = 432.6 - 0.251 x (frt) + c_sac x 240.7 + mn_sac x 54.7 + si_sac x 144 + ti_sac x 398.2 + cu_sac x 77.2 + ni_sac x 173.15 + (n_sac - ti_sac/3.42) x 1794.1 + p_sac x 561.4 - 0.69 x (red) - 1.32 x thick

Model VI: l_tscal = 403.85 - 0.14 x (frt) + c_sac x 575.47 + mn_sac x 63 + si_sac x 113.4 + cu_sac x 60 + ni_sac x 154.9 + (n_sac - ti_sac/3.42) x 2148.9 + p_sac x 531.5 - 0.29 x thick

The terms 'frt' and 'red' above refers to the final rolling temperature and the reduction ratio respectively.

APPENDIX G

GUIDE TO THE USE OF PROGRAMS & NOTES ON PROGRAMMING

APPENDIX G

Guide to the use of Prototype System Developed during the research and Notes on Programming

The system could be run for prototype consultation by either double clicking on the proto2.exe icon in the file manager from the directory in which the software is installed or by typing proto2.exe and pressing enter at the command line in the run sub menu in the file menu. All the supporting files are to be included in the directory from which the program is to be run. The supporting files include the dynamic link libraries (bc30rtl.dll, bc40rtl.dll, pvplus.dll, txdll.dll, xvtw.dll and xvtwtx.dll), the ProtoGen+ library pvplus.lib, the four tableaux rule bases (ch3678.tx, mp3678.tx, char3678.tx and climrule.tx) and the six files for various scroll down menus in the input screens (thick.tab, grade.tab, enduse.tab, spreqs.tab, mattype.tab and value.tab).

Clicking on the proto2.exe icon or running the system from the command line results in the display of a interactive screen having a file menu and an INPUT menu. To commence input to the system click on the INPUT menu. This displays the input screen for basic information regarding customer requirements (Appendix B). Appropriate values could be input in the various fields by tabbing through the fields and either typing the values or by selecting the values from the scroll down menus. The value of thickness, grade and end use could be input by selecting from the scroll down menus. If all the entries in the screen are correct, click on the "OK" button in the screen, other wise the entries could be corrected and the "OK" button could then be clicked. To abandon input of basic information click on the "Cancel" button which displays the interactive screen presented initially. In this screen choosing "Exit" from the file menu aborts the prototype consultation and the file manager is displayed.

Clicking the "OK" button in the input screen for basic information presents another input screen for the customer special requirements (Appendix B). In this screen the values of the three fields could be input by choosing appropriate values from the three scroll down menus. After this, clicking on the "OK" button results in the display of another screen similar to the one displayed earlier for inputting the customer special requirements to enable input of another customer special requirement. This could be continued to input all the customer special requirements and then the "END" button could be clicked to end the input of customer special requirements. This results in the completion of the input process and the system commences the processing of the information input through the two set of screens through the inference engine of the prototype system.

The inference engine of the prototype system utilises various knowledge bases along with the mathematical modelling to generate a list of alternative SACs which could be used to roll the steel plate enquired or ordered by the customer. The system also recommends the SACs which are most appropriate for the customer requirements. These output information are written to files "output.a" and "com&rec.sac" which could be read after the system stops processing input information. The file "output.a" consists of the information about the inputs, the certification limits, modified certification limits and the range of SAC values. Computed and recommended SACs corresponding to the inputs are written to file "com&rec.sac". All the outputs are shown in Appendix A.

The program takes the basic input from the first input screen (basicin.dlg) and the customer special requirements from the three input screens (csrina.dlg, csrinb.dlg, csrinc.dlg). It first retrieves the chemistry and mechanical property information corresponding to the standard number and thickness utilising tableaux rule bases. The chemistry and mechanical property information is modified based on the rules in another tableaux rule base and the IF-THEN rules in the source code. Range of SAC values are determined based on the rules in the "sac_rules" function.

The core function which generates alternative SACs utilising iterative process along with various knowledge bases is “pre_sac”. A database of SACs (sac.c) down loaded from the Technical Specifications System (TSS) is utilised in the function “read_sac” to pick up the SACs from this database which matches the SAC in the SAC list generated by the “pre_sac” function. The function “read_sac” thus recommends SAC(s) from the list of alternative SACs generated by “pre_sac” function. The results of both the functions above are written to file “com&rec.sac” (computed and recommended SACs) and output.a (Certification Limits, Modified Certification Limits and Range of SAC values).