A Knowledge Based Supervisory Support System for Pan Stage Operations in a Sugar Mill

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Statement of Originality

I do hereby declare that this thesis contains no key material, which has been accepted for the award of another degree. Furthermore to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the thesis itself. Parts of this thesis have been published in the papers presented in the list of publications.

The content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program. Any editorial work, paid or unpaid, carried out by a third party is acknowledged. All ethics guidelines and procedures have been followed.

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Roland Dodd

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Acknowledgments

I would like to dedicate this thesis to memory of the late Lucy May James who is my dearly missed grandmother. She thought I would grow up to be a great scientist and I hope to have lived up to her expectations.

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The innumerable hours of toil required in the pursuit of PhD research and the efforts in the furthering of current knowledge are similarly highlighted in the following quote:

"It is not the critic who counts. Not the man who points out how the strong man stumbled or where the doer of deeds could have done better. The credit belongs to the man who is actually in the arena, whose face is marred by dust and sweat and blood; who strives valiantly; who errs and comes short again and again; who knows the great enthusiasms, the great devotions; who spends himself in a worthy cause. Who, at the best, knows in the end the triumph of high achievement, and who at the worst, at least fails while daring greatly, so that his place shall never be with those timid souls who know neither victory nor defeat."

- Theodore Roosevelt, 26th U.S. President (1858-1919)

Contents

List of Figures

List of Tables

Publications List

The results of the research undertaken and reported in this thesis have been published / accepted for presentation by the candidate in the following publications:

Refereed Publications

[1] Dodd, R., Broadfoot, R., Chiou, A. and Yu, X. (2009). Dynamic Allocation of Predicted Quantities to Forecast Intervals for Sugar Mill Pan Stage Operations, *Proc. IEEE International Conference on Industrial Technology,* February 2009, Churchill, Victoria, Australia.

[2] Dodd, R., Broadfoot, R., Chiou, A. and Yu, X. (2009). Pan Stage Steady State Flow Model for Integration within a Knowledge Based Supervisory Support System, *Proc. IEEE International Conference on Industrial Technology,* February 2009, Churchill, Victoria, Australia.

[3] Dodd, R., Broadfoot, R., Yu. X. and Chiou, A. (2008). Process Models for a Sugar Mill Crystallisation Stage Knowledge Based Supervisory Support System, *Proc. Intelligent Production Machines and Systems 2008 Conference*, July 2008, Cardiff, UK.

[4] Dodd, R., Chiou, A., Yu, X. and Broadfoot, R. (2008). Framework for a Smart Supervisory Control System for a Sugar Mill Crystallisation Stage, *Proc. 6th IEEE International Conference of Industrial Informatics*, July 2008, Deajeon, Korea.

[5] Dodd, R., Broadfoot, R., Yu, X. and Chiou, A. (2005). Development of Smart Supervisory Control System in a Sugar Mill Crystallisation Stage, *Proc. Intelligent Production Machines and Systems 2005 Conference,* July 2005, Cardiff, UK.

[6] Yu, X., Chiou, A. and Dodd, R. (2005). A Novel Decision Support Framework for Industrial Processes, *Proc. 31st Annual Conference of IEEE Industrial Electronics Society*, November 2005, North Carolina, USA.

[7] Dodd, R., Broadfoot, R., Yu, X. and Chiou, A. (2005). Empirical Pan Modelling of Vacuum Pans for a Sugar Mill Crystallization Stage, *Proc. Australian Society of Sugar Cane Technologists 2005 Conference*, May 2005, Bundaberg, Australia.

[8] Dodd, R., Broadfoot, R., Yu, X. and Chiou, A. (2004). Update on the Development of a Smart Supervisory Control System for Pan Stage Operations in Sugar Factories, *Proc. 2004 Regional Research Seminars,* March 2004, Mackay, Australia.

[9] Dodd, R., Broadfoot, R., Yu, X. and Chiou, A. (2002). Development of a Smart Supervisory Control System for Pan Stage Operations in Sugar Factories, *Proc. Information Technology in Regional Areas 2002 Conference*, August 2002, Rockhampton, Australia.

Abstract

The recent downturn in world sugar prices has placed even greater demands upon the Australian sugar industry to reduce the costs of sugar manufacture and increase the consistency of producing high quality sugar. One of the proposed approaches in increasing the consistency of very high quality sugar production and leveraging further avenues for cost saving is in the development of a computer based advisory system. This system is able to provide expert knowledge in the area of pan stage management and best practices in the absence of human experts. This thesis explores the design, key features and outcomes of a knowledge based supervisory support system (KBSSS) framework proposed specifically for providing cooperative decision support in the area of pan stage operations within a sugar mill. To demonstrate the viability of the proposed KBSSS framework a prototype system was developed in accordance with the proposed framework.

The KBSSS utilises three core innovative system technologies that form the core components of the proposed KBSSS framework. These technologies are: 1) *Dynamic industrial pan stage process models* for identifying the dynamic relationships between sections of pan stage operations to allow for future forecasting of pan stage operating conditions, 2) *Integration techniques for the merging of the developed pan stage process models into the hybrid fuzzy logic expert system rule base* to provide localisation adjustment to match with local real world factory operational conditions, and 3) *Explanatory capabilities* to provide justification and support of system advice and recommendations.

As a result of research and development carried out in this thesis, the KBSSS's test results demonstrated in the thesis indicate the viability of the proposed KBSSS framework and highlight the forecasting capabilities of the developed system resulting in favourable outcomes compared to data from pan stage operations. As a result of the research undertaken in the thesis a prototype KBSSS, for pan stage operations, based upon the three core supporting intelligent system technologies reported in the thesis has been developed.

Chapter 1: Introduction

1.1 Introduction

Improved pan stage best practices and management has the potential to help reduce the costs of sugar manufacture, increase the consistency of producing high quality sugar and assist in broadening the revenue base of sugar factories through measures such as the cogeneration of electricity. Economically such improvements have the potential to make saving of $250,000 annually per sugar mill with additional non-estimated financial benefits from cogeneration of electricity through steam saving (Yu and Broadfoot, 2001).

The resolution to solve this problem is in the provision of expert advice on best practice and management strategies of pan stage control. However this advice is not readily available. Further problems result from the complex nature of pan stage operations with no overall view of entire operations being available. This problem is further exacerbated by pan stage operators often not having specific backgrounding in chemistry to adequately understand the sugar making process.

Due to the relatively large number of Australian sugar mills, the vast distances between mills, the long crushing season duration and continuous round the clock processing, the limited availability of human experts in this area means that it is not feasible for such experts to constantly monitor pan stage operations or provide specialist assistance to pan stage operators. Such experts are a scarce commodity.

With consideration of these factors, there is definite need of a system for providing expertise in sugar mill pan stage operations.

1.2 Objectives

To explore the viability of a knowledge based supervisory support system (KBSSS), this thesis examines a framework proposed and designed specifically for providing cooperative decision support for pan stage operations in a sugar mill. In order to demonstrate the merits and feasibility of the approach, a prototype advisory system for the advice of best practices and management of the pan stage is developed incorporating several innovative software technologies as part of a hybrid fuzzy logic based expert system architecture that supports several complementary intelligent system technologies. This system adheres to the design principles of the proposed KBSSS framework.

These innovative technologies, as reported in the thesis, are:

1. Pan stage process models for identifying dynamic interrelations between sections of pan stage operations to allow for future forecasting of pan stage operating conditions;

2. Integration techniques for merger of the developed pan stage process models into a hybrid fuzzy logic based expert system rule base; and

3. Explanatory capabilities for hybrid fuzzy logic based expert system advice and recommendations.

Collectively these technologies will allow for the development of a KBSSS that is able to deliver reliable advice for consistent and more optimal control actions by pan stage operators.

The dynamic pan stage models describe segments of the overall pan stage industrial process. Together these models work together to collectively realize a unified mechanism to allow for forward prediction of future operating conditions. Fuzzy logic allows localized refinement of the process models that are integrated into the fuzzy logic rule base, to match current factory operating conditions. Such conditions are not available in the static knowledge base. Explanatory capabilities provide justification for recommendations and advice offered by the system and aid in their acceptance by end users.

1.3 Significance

The findings in this thesis will contribute to a better understanding of the possibilities and capabilities of the proposed KBSSS and its associated framework. It will also demonstrate the viability of the integration of several different kinds of innovative intelligent system software technologies that are capable of forecasting of pan stage operating conditions and provide expert advice in the absence of human experts.

Experts are not available to provide specialist assistance to pan stage operators. Due to the relatively large number of Australian sugar mills, the vast distances between mills, the long crushing season duration and continuous round the clock processing, the limited availability of human experts in this area means that it is not feasible for such experts to constantly monitor pan stage operations. Decision support from experts is unable to focus on operational assistance or in the provision of operational strategies for specific sugar mill locations. Experts are a very scarce commodity.

Prior specifications (Dodd, Yu, Broadfoot and Chiou, 2002) acknowledge that an expert advisory system is unavailable in the area for providing expert advice in best practices and management of pan stage operations within a sugar mill industrial environment. Therefore, in adhering with these development guidelines, the development of the KBSSS is one means of contributing to the solution of optimal control and advice in the absence of human experts for pan stage operations.

Currently, there is no such knowledge based supervisory support system for pan stage operations neither in the Australian sugar industry nor in the world sugar industry. This research will make a significant contribution to the development of a pan stage supervisory support system for the sugar industry that will reduce the cost of sugar production and also result in increased quality of sugar products. The KBSSS will directly increase the financial returns for the sugar industry and improve the long term, economically sustainable position of the industry.

There is an increasing need for a supervisory support system for pan stage operations as:

1. Factories are placing an increased range of duties on operating staff. Staff are supervising a wider range of processing operations. A reduction of in staff numbers is a response to the increased economic pressures being placed on factories;

2. The production of premium quality sugar now attracts a substantial financial bonus as part of an overall plan to improve Australia’s sugar marketing position;

3. The large price disparity that exists between sugar and by-product final molasses results in increased financial benefit for improvements in pan stage crystallisation yield; and

4. Many factories are seeking to reduce their steam consumption for raw sugar manufacture in order to maximise their export of electricity through cogeneration and so achieve additional revenue.

The atypical KBSSS specifications require substantial extension of the conventional fuzzy knowledge based system framework to include novel components such as meta consequents (Chiou and Yu, 2007c) so that discourse advices and explanation to justify control actions can be provided. Such extensions are required for the system interaction with dynamic pan stage interrelation industrial process models, explanation functionality for operators and integration of linguistic expressions of human knowledge with numerical measurements.

To the best of the current research knowledge, the research undertaken has a complexity that has not been addressed before within fuzzy system theory. The development of the knowledge based supervisory support system will further enrich the understanding of fuzzy logic rule based expert/knowledge systems and provide practical benchmark solutions by integrating several intelligent systems paradigms to work cooperatively to address an important industrial problem.

The knowledge based supervisory support system would be applicable to all Australian sugar factories. It would also have application to several overseas sugar industries in the future. These applications would most likely be after the implementation within Australian sugar mills. In addition, the extended fuzzy knowledge based system framework is applicable to other industrial processes such as food processing and chemical processing that require better coordination of operators for consistent quality products and high efficiency.

1.4 An Overview of the Proposal, Design and Development Stages

The research presented in this thesis demonstrates the viability of the proposed KBSSS framework through the design, implementation and testing of the developed knowledge

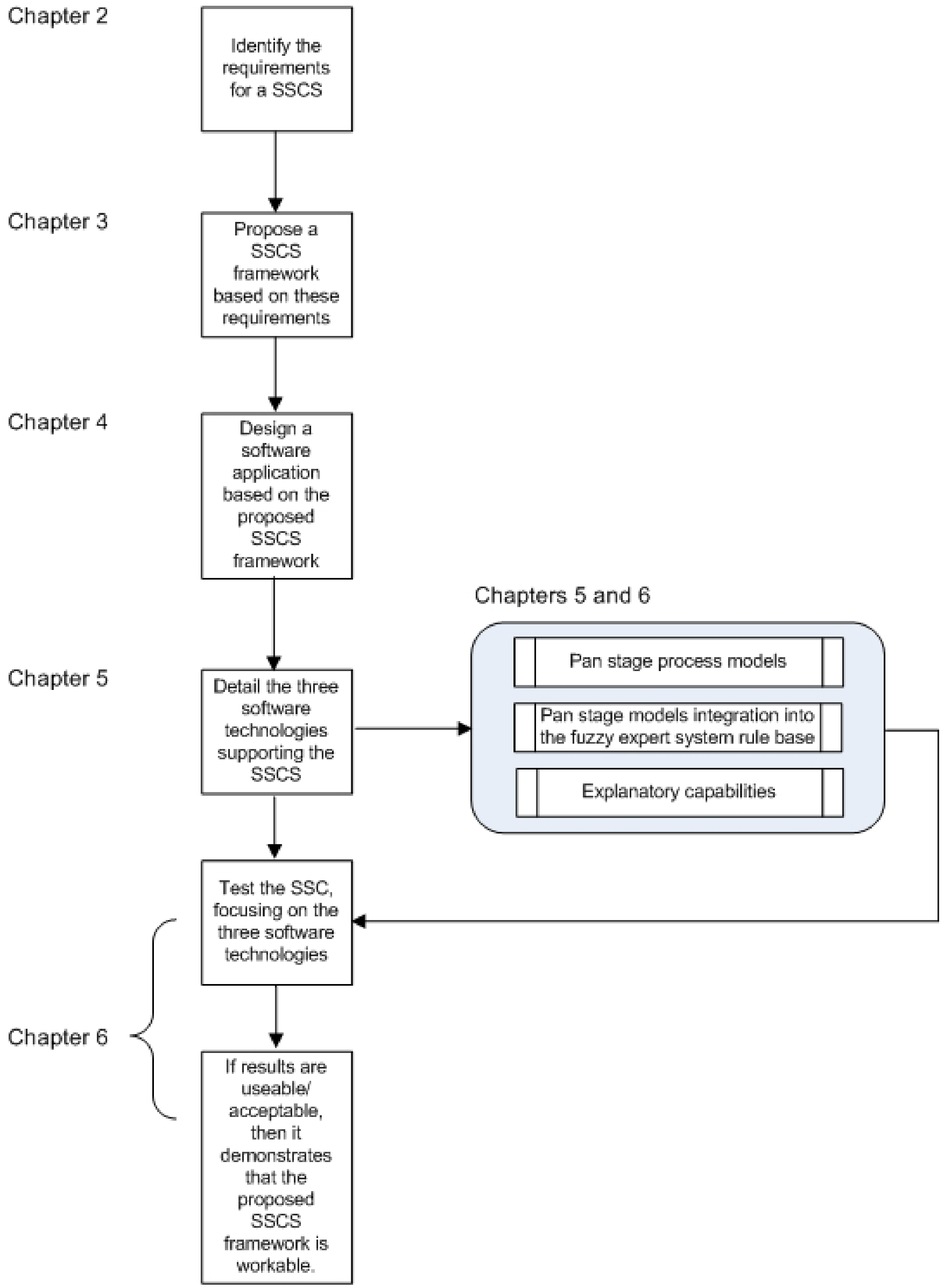

Figure 1: Overview of the design and implementation stages for the methodology reported in the thesis.

based supervisory support system software. As defined previously, this system will be primarily supported by three software technologies. These technologies are designed specifically for the hybrid fuzzy logic based expert system that the overall design is based upon. The overview of the proposed KBSSS framework, implementation and testing stages in the thesis are shown in Figure 1.

1.5 Synopsis and Organisation of the Thesis

This thesis is divided into seven chapters. Chapter 1 is an introduction to the overall thesis presenting the objective, significance and structure of the thesis. The thesis structure follows the methodology and topics presented in Figure 1. The rest of chapters are organized as follows:

Chapter 2 provides a review on pan stage operations and associated problems. The review will also further outline the need for a KBSSS and detail fundamental requirements and expectations of such a system. Historical approaches and their results will also be presented. Incorporation of the identified factors within the KBSSS framework should help overcome current pan stage operational problems and limitations.

In Chapter 3, the framework for the KBSSS is detailed along with the general supporting principles behind the proposal. Layered architecture and framework are presented along with explanation of the key features.

The purpose of Chapter 4 is to describe the overall system design of the KBSSS. This chapter details how the three core innovative system technologies, 1) pan stage process models for identifying dynamic interrelations between sections of pan stage operations to allow for future forecasting of pan stage operating conditions, 2) integration techniques for merging the developed pan stage process models into a hybrid fuzzy logic based expert system rule base, and 3) explanatory capabilities for hybrid fuzzy logic based expert system advice and recommendations, are integrated into the hybrid fuzzy logic based expert system.

Chapter 5 explains the method and integration of the three core innovative supporting features of the KBSSS in detail. The section on the dynamic interrelation industrial pan stage models describes the series of developed models used to predict future pan stage operating conditions. This is followed by techniques for the integration of these developed models into the fuzzy logic rule base with adaption for local operating conditions. The final section describes the mechanics of the explanatory capabilities employed within the KBSSS.

In Chapter 6 the testing of all system features is demonstrated. Real world pan stage control system data is used as the primary system input. Case study results are presented in this chapter with system output used to asses the performance and capabilities of the KBSSS. System output of recommendations and explanations are demonstrated.

Finally, this thesis concludes with Chapter 7 presenting conclusions and areas for further research.

1.6 Glossary of Terms

The following terms are commonly used in the thesis. Although the terms (Queensland Sugar Corporation, 1997) pertaining to the Australian sugar industry are commonly used, there is some variation in their meanings due to industry variations among countries, overseas mills and refineries.

Bagasse. The final crushed sugar cane fibre remaining after milling.

Brix. A unit used to express the concentration of solids in aqueous sugar solutions.

CCS. Commercial cane sugar. CCS represents the sugar content of cane as it is purchased by sugar mills.

Fibre. Fibre is the cane plants vegetable skeleton in which juice is stored and through which plant food, dissolved in water, is distributed throughout the plant. In the milling process, the fibre cells are ruptured, thus freeing the juice.

Final molasses. The black syrup, commonly known as molasses or 'C' syrup, remaining after the sugar syrup has been boiled and passed through the centrifugal for the last time in a sugar mill or refinery. The sugar it contains cannot be removed economically.

Hybrid system. Hybrid systems generally involve multiple individual artificial intelligence technologies that are either used in series or integrated in such a way as to produce advantageous results through synergistic interactions.

Juice. Cane juice consists of water with sugar and other substances dissolved in it and a portion of insoluble particles suspended in it.

Knowledge based supervisory support system (KBSSS). The developed hybrid fuzzy logic expert system incorporating dynamic pan stage relational models as part of the rule base and in tandem with explanatory capabilities.

Magma. The mixture produced when sugar crystals and syrup are combined together.

Massecuite. The mixture of crystals and syrup produced by crystallisation in a vacuum pan. The term is French for "cooked mass".

Pan stage. Also known as the "crystallisation section" of the sugar factory. This portion of the factory is where the process of growing the sugar crystals is undertaken in vacuum pans.

Polarisation (pol). An estimate of the sucrose content of sugar.

Sucrose. Commonly referred to as sugar. A carbohydrate having the chemical composition of $C_{12}H_{22}O_{11}$. It comprises two simple sugars – glucose and fructose.

Syrup. In the milling process syrup is the name of the product stream after it leaves the evaporators and before it enters the pans.

Vacuum pan. Cylindrical steel vessels in which a steam heated surface is used to boil sugar syrups under partial vacuum at relatively low temperatures.

1.7 Summary

This chapter has introduced the problem of pan stage control for industrial operations within the sugar mill setting. As a result of this problem, there is need for the development of a knowledge based supervisory support system. This system will eventually be used to help provide recommendations for improved pan stage control and management. An overview has been provided to show the methodology for the proposal, design and development stages reported in the remainder of the thesis. The structure of the thesis has also been outlined.

In the next chapter, the literature review for the research area will be presented. This will include a review on pan stage operations and associated problems. The review will also further outline the need for a KBSSS and detail fundamental requirements and expectations of such a system. Historical approaches and their results will also be presented. Incorporation of the identified factors within the KBSSS framework should help overcome current pan stage operational problems and limitations.

Chapter 2: Review on Background to the Research

2.1 Introduction

This chapter establishes the fundamental basis for the research carried out in the thesis. It describes the problem of pan stage management within the sugar mill factory environment and the approaches undertaken in an attempt to work towards to an overall solution. The remaining sections will discuss the background of decision support with the identification of limitations for the current approaches to pan stage control and management. Several suggested improvements are introduced that form the basis for a proposal of a knowledge based supervisory support system for pan stage operations in a sugar mill setting.

This chapter is organized as follows. Section 2.2 provides a review of the economic significance of Australian sugar production. Section 2.3 provides an overview of the process of sugar production for a sugar mill. Section 2.4 then follows describing the process by which sugar crystals are grown within the pan stage crystallization section of the sugar mill. Section 2.5 provides a comprehensive review of attempts to pass expertise and knowledge to stakeholders with focus on the existing decision making process along with traditional approaches to models used to describe the overall pan stage process and early attempts in attempting to provide an overall solution for pan stage management and control. Section 2.6 identifies several weaknesses that are evident in current approaches for decision support operations for the pan stage. Section 2.7 outlines improvements required in the provision of a knowledge based supervisory support system framework and Section 2.8 outlines the scope of the thesis.

2.2 Economic Significance

Sugar production is one of Australias major export industries employing directly in excess of 17,000 people in the areas of growing, milling, storage, marketing and refining of raw sugar with a further indirect employment of 24,000 people (Queensland Sugar Corporation, 1997). The Australian sugar industry provides a major economic base for rural and regional areas. Australia's sugar producing region stretches from Mossman in far north Queensland to Grafton in northern New South Wales. The sugar industry processes in excess of 35 million tonnes of cane annually, producing in excess of 4.75 million tonnes of sugar. Exports amount to around 80% of the total sugar production. The sugar industry is heavily dependent on achieving cost effective operations in order to compete in the global sugar market (Canegrowers, 2008a).

The production of sugar of very high quality is essential in order for Australia to maintain a favoured market position. During the period 1998 to 2000 the world price of sugar more than halved from US12c/lb to US5c/lb. With the price somewhat restored to US10c/lb as at July 2008 (Canegrowers, 2008b), enormous pressures have mounted on the Australian sugar industry to:

(i) reduce the costs of sugar manufacture;

(ii) increase the consistency of producing high quality sugar; and

(iii) broaden the revenue base of sugar factories through measures such as the cogeneration of electricity

The impact, due to the recent sharp decline of world sugar prices, on the regional economies of coastal Queensland and northern New South Wales clearly highlights the importance of the sugar industry to these regions and to Australia as a whole. The strong dependence on export earnings means the sugar industry's viability in competing in the free world market for sugar depends heavily on cost competitiveness. Research, and the development and implementation of new techniques, processes and equipment designs have played a significant role in keeping the Australian sugar industry as one of the worlds lowest cost sugar producers (Yu and Broadfoot, 2001). The low world sugar prices, which currently exist, place further real pressure on the industry to find more avenues for cost saving and increases in revenues.

The research to develop a knowledge based supervisory support system for pan stage sugar processing operations, as outlined in the thesis, is one such example of the way the industry has responded to these pressures through developing solutions to reduce costs and boost revenue. Such research improves the economic strength of the industry and allows it to remain a competitive force in world trade.

Recent financial incentives and changes due to the new raw sugar quality scheme standards (Queensland Sugar Corporation, 2003) introduced for the 2003 sugar season, and beyond, give premium bonuses and add extra financial incentive for the production of high quality sugar.

2.3 A Review: An Overview of Sugar Production

The standard operation of a sugar factory involves the processing of large quantity of canes for the purpose of sugar production. An overview of this process (Queensland Sugar Corporation, 1997) is now presented. The process is as follows:

After harvesting, cane is transported to the mill where it is weighed and processed at an automated cane receival station. Information on the producing farm along with the weight of each cane bin is automatically recorded at the cane receival station. Bins of cane may be transported to the factory via lorry or tram system. A series of cane bins from a particular sugar farm location are collectively known and processed as a “rake”.

Within the sugar mill setting the bins of cane are sequentially feed to the shredder via a cane carrier system. The shredder disintegrates the cane and breaks it down into a fibrous material while rupturing the juice cells. An analysis of the first expressed juice of the cane allows the determination of the sugar content of the cane and associated payment to the canegrower depending upon the juice characteristics. Pairs of rollers feed the cane through a series of mills. Each mill consists of three large rollers arranged in a triangular formation. This process separates the sugar juice from the fibrous bagasse material. The bagasse is used as fuel for the boiler furnaces and the juice is pumped away for further processing.

There are two main methods of analysis of the composition of the rakes. The traditional method is to send a sample of the first expressed juice from the first rolls of the mills to the juice laboratory for analyses. The juice from a rake is composited so only one sample is analysed. Factories are also moving to the use of near-infrared spectroscopy measurement on the cane in the chute to the first mill. Measurement by near-infrared spectroscopy is undertaken continuously but the result for a rake is combined to provide a single analysis for the entire rake.

The juice extracted by the crushing mills contains impurities. These impurities are removed through the addition of lime and then by further heating the juice. The added lime assists in neutralizing the acids and to precipitate the impurities. The process coagulates the impurities into “flocs” of mud which then settle in large vessels known as “clarifiers”.

Muddy juice extracted from the bottom of the clarifiers is mixed with fine bagasse material and then filtered using vacuum filters to recover the sugar. The mud and bagasse mix that is extracted by the filters is recycled for use as fertilizer. Such recycling allows use of the phosphorous rich material that is left over. This phosphorous having been taken up from the soil by the cane plant during its growth.

The clear juice from the clarifiers is then further concentrated. This process is undertaken in a series of connected vessels called “evaporators” by boiling the juice under vacuum. The resulting concentrated juice is known as “syrup”. The syrup is concentrated by boiling in a vacuum pan and is seeded with small sugar crystals in a process called “crystallization”. The sugar crystals are grown to the required size by adding more syrup and molasses while the boiling process continues. This mixture of syrup and crystals is called “massecuite”. The massecuite is discharged from the pan when the crystals reach the required size.

Molasses is separated from the raw sugar crystals in the centrifugals. A centrifugal consists of a perforated basket within a casing and spins at very high speed. The molasses surrounding the sugar crystals passes through the perforations in the basket and is separated. The molasses that is spun off is recycled back into the crystallisation process and boiled again allowing the recovery of more raw sugar crystals. This procedure is repeated until the amount of sugar obtained from the molasses is too small to be economical for further processing. The product molasses, also known as “final molasses”, is the syrup left over from the last and final centrifuging process. This is stored for later sale. The raw sugar separated by the centrifugalling process is then dried and transferred for storage at the sugar mill.

Through this series of operations the sugar cane is processed by the mill with resulting products of final molasses and product sugar. The byproduct bagasse is used to fuel the sugar mill boilers and the byproduct mud recycled for use as fertilizer.

2.4 A Review: Pan Stage Operations in Sugar Milling

Raw sugar production from cane sugar is an essentially continuous operation. Sugar processing extends through 120-168 hours per week over 20-25 weeks of the harvest season. Cane is crushed to extract juice which is then clarified to remove impurities. The juice is evaporated at reduced pressure and temperature to give a concentrated liquid known as “liquor”. The liquor is pumped to a syrup storage tank in the crystallisation section of the factory.

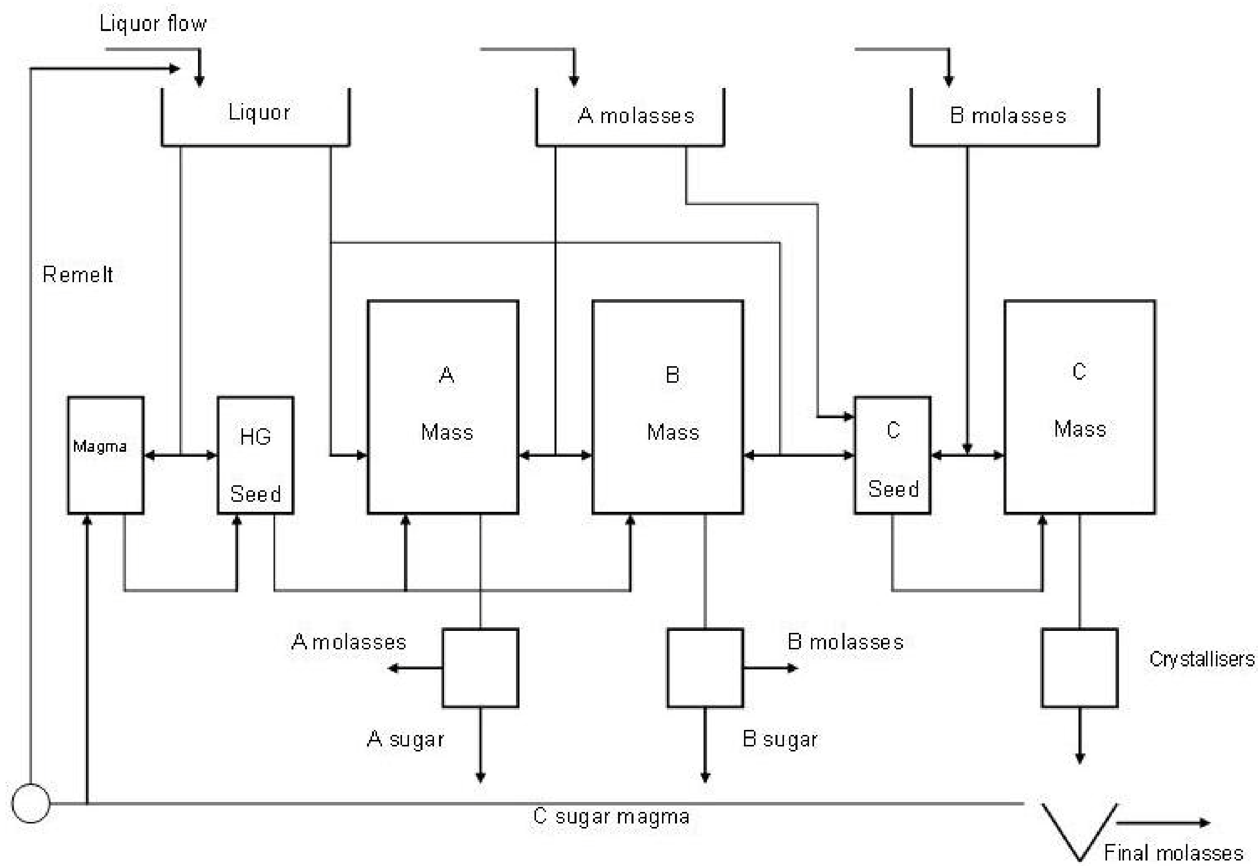

Figure 2: An overview of pan stage operations showing process material flows and interactions.

From the initial point of unloading of the sugar cane bins through to the syrup tank of the pan stage, the processing operation is essentially continuous. Buffer tanks interspersed between equipment items helps in reducing flow variations effects that can occur as a result of many often interacting factors which include the batch and continuous processing styles utilized by equipment on the pan stage.

The crystallisation section, as shown in Figure 2, is commonly referred to as the "pan stage" and is the most complex stage of the overall sugar factory process. Several batch wise and continuous crystallisation steps take place concurrently within this part of the process. Feed forward and feedback recycle streams are superimposed on this series of operations. The final stages in the raw sugar factory are the centrifugal station, which separates the sugar crystals from the mother liquor, and the sugar drying station (Broadfoot and Beath, 1998).

In current practice, two operators are normally employed on the pan stage and their duties normally do not extend any further than this section. There is considerable process interaction between the pan stage and centrifugal stage although management of the centrifugals is undertaken by different operators. The overall strategic management of the pan stage is quite difficult because of the large range of process streams of varying compositions and crystal growth rate characteristics that must be managed (Miller and Broadfoot, 1997).

The crystallisation process takes place in large batch fed vessels known commercially as "batch vacuums pan", in continuous vacuum pans or in batch and continuous stirred cooling vessels referred to as "crystallisers". Typical factories have between six and ten of these pans and about sixteen hours of residence time in the crystallisers. The pan stage has an input stream of syrup and intermediate molasses recycle streams. The resulting output products from the pan stage are raw sugar and final molasses.

As part of short term storage solutions for process streams, stock tanks for syrup and molasses are used as buffers between equipment items on the stage. Over the long term however these temporary storage measures cannot be used to overcome differences in interactions between various parts of the factory given the batch and continuous type processes that already take place within the pan stage. Stock tank levels rise and fall over time due to the supply and demand of feed materials that they store at different points in the overall pan stage schedule. At extremes, undesirable outcomes include the stock tanks becoming empty or overflowing. These conditions require serious remedial actions with possible processing obstructions and factory shutdown until such problems are solved.

In comparison to juice flow control, where it is possible by incremental adjustments to progressively change the long term average flow rate, such corrective actions are not possible on the pan stage. Pan stage decisions often need to result in precise and definite action, as a result of batch processing operations. Errors in the decision making process often cannot be corrected and may result in severe disruptions to processing for extended periods. Such hold ups in the continuous pan stage processing environment which operates around the clock also has substantial financial impacts.

The use of stock tanks as buffer storage is due to the irregular nature of pan stage operations, particularly the mixed nature of mixed batch and continuous processing that occurs concurrently along with the need for temporary process stream material storage for interaction between juice processing and the centrifugal station sections with the pan stage. Within the pan stage stock tank levels change as a result of centrifugal station operations and the allocation of individual vacuum pans to specific scheduled production duties.

In the decision making process it is important to recognise when process material stock tank level require a change in operational strategies in order to realise improved factory process throughput rates and to avoid the previously described problems. Given enough instrumentation and computer based resources it is theoretically possible to specify the complete operating state of the overall pan stage, including stock tank levels, at any given point. However the high implementation costs and complexity of such an approach make this unfeasible for practical purposes (Miller, 1987).

The sugar content and purity characteristics of the sugar cane received by a factory also have a strong influence on pan stage operations and in particular the production loadings on different equipment on the pan stage (Broadfoot and Pennisi, 2001). Often the pan stage is managed in a sub-optimal manner because an overview of operations encompassing various sections – cane receival, juice processing station, the pan stage and centrifugal station – is not available.

2.5 A Review: Decision Support for Pan Stage Operations

Currently there is no such known supervisory support system in existence for pan stage operations which fulfils all known system requirements and objectives that are presented in this chapter nor based upon the intelligent expert system based approach. However, fragmented attempts have been made in solving portions of the overall problem. The following subsections will elaborate on these approaches in further detail.

2.5.1 Existing Decision Making Process

An overall encompassing view of the various section of the factory is not available and hence operators are not able to predict future pan stage loadings. Computer based prediction facilities are not available as a consequence of operators actions. The only available predictions are the actual forward estimates the operators intuitively carry out.

Due to the lack of an overall view of pan stage operations in relating this area to other sections of the sugar factory, the overall pan stage complexity and no facility of forecast of operations, pan stage management is generally carried out as a reactive approach in responding to problems in operation rather than a proactive approach enabling avoidance of problems and more optimal strategic management. Decisions are often not based upon an analytical approach. Instead decisions are most likely based on and affected by the experience of the current pan stage operators on shift.

Decisions and control actions often suffer from the personal bias and the mental models operators have of the pan stage and in management of the crystallisation process. This can lead to differences between best practices and actual onsite practices. The pan stage is usually accepted as the most difficult process area for new operators to master. There are many interacting factors and problems that can arise and it is often difficult to achieve a full understanding of the process (Sugar Research Institute, 2001).

Pan stage sugar boilers may not have a chemistry background in order to best understand the process of sugar production. This leads to reliance on training received during pan boilers courses and *on the job* training. Understanding the theory behind the processes of pan boiling and scheduling and knowledge of the variables which are important for optimal productivity are vitally important for the role.

Due to the pan stages considerable interaction with the centrifugal station, the pan stage operators work in close partnership with the centrifugal operators. The existing decision making process is reliant upon the operating decisions and actions that operators make. Typically pan stage operators and supervisors are required to constantly estimate future flows on the pan stage along with available levels of feed materials held in stock tanks. They intuitively have to account for current stock tank levels and use their knowledge of pan stage processes, along with current and likely future decisions to reach a conclusion on the outcomes of future levels given likely feed quantities over the projected forecast period. This problem is further exacerbated by the forward look ahead process. Pan stage operators will typically be trying to forward estimate not only for their current shift but also into the next operators shift as well.

This scenario is similarly evident for operators selecting duties for swing pans (Broadfoot, 2003b). Determination of swing pan duties is intuitively performed by operators under the previously presented circumstances. Selection problems can be attributed to overall operator concerns of particular stock levels and can lead to favoured duties instead of the most appropriate decision for optimal production.

Factories are placing an increased range of duties on operating staff. Staff are being required to supervise a wider range of processing operations. Furthermore, a reduction of staff numbers in the foreseeable future is a response to increased economic pressures on factories. With fewer staff available the decisions of each operator become more critical in smooth factory operation. Furthermore, when experienced operators leave or retire, factory performance suffers as a consequence of a new operator learning to perform their role.

2.5.2 Early Attempts in Providing a Resolution

A seminal work in the establishment of an advisory system for pan stage operations was attempted at Racecourse mill (located in Mackay, Australia) over three decades ago. A supervisory control system was proposed with implementation on early computer systems (Frew and Wright, 1976; Frew and Wright, 1977). Given the major limitations of early computer technology, programming language capabilities and factory instrumentation a rudimentary advisory system to provide guidance to pan stage operators was attempted.

Due to these limitations this scheme was not carried through to fruition although the trial demonstrated the merits of the approach.

An early proponent (Watson, 1989) suggested the development and application of expert systems to pan stage decision support and control. Potential benefits were recognised to be: 1) greater confidence in correct decision making and minimisation of time lost due to operational errors, 2) less idling of batches therefore saving steam and improving sugar quality, and 3) earlier warning of overload on the crystallisation stage. It was noted that there was no known expert system implementation for pan stage operations.

A shift supervisor advisory system with application to the juice clarification area in a sugar mill was reported by Pozzetti (1996). The system was designed to support the role of shift supervisor and offer advice on process operations, trouble shooting and equipment characteristics. Guidance was provided through the provision of decision trees in the determination of advice.

Only one other known instance of a support system for a sugar factory has been reported in literature (Van Wissen, Smeets, Muller and Verheijen, 2003; Verwater-Lukszo and Van Wissen, 2003; Verwater-Lukszo, Verhofstad and Sturm, 2003). The support system was developed for a beet sugar factory in the Netherlands. A recipe based system working in tandem with a modified Model Predictive Control system (Van Wissen, Smeets, Muller and Verheijen, 2002) and a modified mass balance model of the pan stage incorporating energy flows of the pan stage was used to provide assistance for scheduled activities. This system was limited to offering advice solely for a single continuous B massecuite production pan on the pan stage and was not based upon an expert system approach.

2.5.3 Orthodox Approaches

Fairly limited research has been carried out into models that can be used to relate together the various sections of the pan stage. Attempts have been made into solving smaller portions of the overall problem.

The fundamentals for the sugar crystallisation process are well understood. A substantial and detailed review of the fundamental principles of the crystallisation process, crystal growth, pan strike control and management were reported by Wright (1983). Wright described the basic principle of crystal growth and nucleation for vacuum pan boiling. The major principles of pan strike control, sequencing, pan turn around automation and pan stage management automation were detailed.

Limited research carried has been out into stock tank models. Previous approaches were reliant upon stochastic prediction methods (Miller, 1987; Miller, 1988) for level forecasting with limited forecast period and being based solely upon historic level data.

Historically mass balances (Bureau of Sugar Experiment Stations, 1984) of the overall sugar factory have been used to determine the average production rates of process streams. While such information carries strategic value in assessing factory operations and performance characteristics it gives no insight into the internal works of the pan stage or allow for any form of predictive capabilities. Mass balances are carried out, as is typical for regional Queensland based mills, on historic data that is typically clustered into weekly data segments for an entire crushing season (Mackay Sugar Cane Association, 1995; Mackay Sugar Cane Association, 2002c; Mackay Sugar Cane Association, 2002b; Mackay Sugar Cane Association, 2002a).

The prediction of the quantities of sucrose and impurities in syrup from cane receival information allows a forward forecasting of the future pan stage loading of syrup which is of vital modelling importance since liquor comprises the basic input to the pan stage. Previous research into predicting the impurity loading to the pan stage was based on assigning impurity losses to factory product streams. These assessments (Broadfoot and Miller, 1990) demonstrated huge variability in the estimate of pan stage syrup impurities by ±20% during successive weeks of factory operation. Conventional methods for factory sucrose and impurity balances (Bureau of Sugar Experiment Stations, 1984) also exhibited substantially large variations in the estimate of the sucrose and impurity quantities in syrup to the pan stage.

Factory technical performance indices (Steggles, 1997) are also inadequate for prediction of liquor quantities from cane receival data. The technical index is essentially a historical performance function involving the estimation of the *virtual* solids liquor flow rate and the *virtual* liquor purity from cane supply analyses. The actual sugar production is compared with the estimate from this *virtual* liquor composition. The technical index is a series of linear equations that have been developed to estimate the virtual liquor composition from the cane supply data. However this approach is totally reliant upon historic data in order to calculate previously weekly factory performance and as such is unsuitable to be used in a predictive manner (Broadfoot, 2003a).

Earlier research into the determination of vacuum pan feed rates has previously been studied through the experimentation of vacuum pan's operation and by mechanistic modelling of batch/continuous pans (Broadfoot, 1980; Wilson, Kapur, White and Lee, 1987; Miller and Beath, 2000; Schneider, 2003). However such approaches are overly complex for expert system integration with increased requirements for additional vacuum pan instrumentation and associated information sources.

Models of overall pan stage sugar production (Wright, 1996; Broadfoot and Pennisi, 2001) are available however lack the localisation required for prediction of specific pan stage stock tank levels or process feed streams at a future point in the overall pan stage schedule. Such models are very broad based and focus on overall production of the stage with reliance on long term steady state pan stage flow quantities and purities for varying boiling schemes. These models are useful for overall pan stage modelling and prediction of average production quantities under seasonal conditions, however they lack specific localisation required for prediction at a low level resolution and on a time scale basis.

Fundamental research using a set packing method for optimising the scheduling of pan stage operations was carried out by Nott and Lee (1999) which has led to further extension of multi-objective pan stage schedule optimisation using genetic algorithms (Shaw, Lee, Nott and Thompson, 2000). This optimisation approach of pan stage scheduling was an attempt to unify batch and continuous processing modes. However problems with the varying importance of processing objectives throughout the crushing season were evident as seasonal conditions require a modification to processing objectives throughout the cane crushing period. Research outcomes however demonstrated the merits of the approach and the inherent problems needing to be solved.

2.5.4 Transfer of Knowledge and Expertise

The generated result of research and cumulative expertise in the area of pan stage best practices and management calls for a medium to facilitate its transfer from these agencies to the factory sugar mill pan stage environment. Several notable early attempts were made (Frew and Wright, 1976; Frew and Wright, 1977; Van Wissen, Smeets, Muller and Verheijen, 2003; Verwater-Lukszo and Van Wissen, 2003; Verwater-Lukszo, Verhofstad and Sturm, 2003). However a best practices and management system using intelligence expert system based technologies will improve outcomes for stakeholders (Watson, 1989) and aid in efficiently disseminating knowledge. This will result in better pan stage control and management outcomes as presented previously in Chapter 1.

The Sugar Research Institute (located in Brisbane, Australia) forms one of the research partners in the provision and development of a KBSSS. The Sugar Research Institute is Australia's premier sugar processing research and development specialist, with specialisation in sugar milling, power generation, sugar refining and sugar chemistry. The Sugar Research Institute works in close partnership with sugar industry members and conducts extensive research programs for clients. It offers a range of commercially available consultancy services, contract research and development, along with factory equipment designs and products to assist clients in improving productivity and factory performance (Sugar Research Institute, 2006). As a result of these collaborative research efforts to achieve practical research outcomes for clients there is a need to transfer this gathered knowledge to the stakeholders in the provision of a KBSSS. Experts in such an organisation are a scarce commodity and there is competition for the availability of such finite resources.

2.6 Unrealised Expectations for Decision Support in Pan Stage Operations

In assessing both the historic and current approaches to solving the problem of pan stage decision support several common themes are evident highlighting weaknesses and limitations.

These factors are:

1. Limitations of existing pan stage process models;
2. Reliance upon discrete algorithms and precision based systems;
3. Dependence upon rigid software system input data;
4. Lack of qualitative reasoning mechanisms;

5. Reactive approach to decision making;

6. Computerised outcomes without proper explanation or justification; and

7. Overly large scale application.

The following subsections will elaborate on these in further detail.

2.6.1 Limitations of Existing Pan Stage Process Models

As presented earlier in Section 2.5, some attempts have been made to develop process models establishing relationships for the internal workings of pan stage and its interaction with other parts of the overall sugar factory. However use of such existing models is limited in the context of development of a KBSSS. Typically these models suffer from:

1. either not adequately relating or not working towards relating the pan stage, and its interconnected factory sections, to the required level of detail; or

2. not being implemented upon a time scale basis.

This leads to such models being unsuitable and/or unworkable for implementation in providing a forecast of pan stage operating conditions over a prediction period.

Existing process models are relatively limited and not well suited for the prediction of loadings on the various equipment items in the pan stage. Due to the recognised complexity of the pan stage environment, adequately suited process models to describe both the internal pan stage features as well as the interactions between the pan stage and the rest of the factory are a fundamental requirement for pan stage decision support.

2.6.2 Reliance on Discrete Algorithms and Precision Based Systems

The algorithmic processes within software system operate upon and are reliant upon the precision of the data entered into the system. Such operation provides limited user interaction and does not provide the facility for human interaction in shaping system inputs.

Mechanisms for providing heuristic based information are not available as part of information processing nor able to influence reasoning capabilities of the underlying software. Current approaches are very inflexible as to the range of system input able to be provided which limits overall system interaction.

2.6.3 Dependence on Rigid Software System Input Data

Software systems are reliant upon the validity and occurrence of data used as inputs. Data of the correct input specification is of critical importance for correct software functionality. Due to the heavy software dependence upon inputs provided, this leads to a very structured process and limiting for useability in terms of a truly flexible system for user interaction. Users are unable to specify new quantitative or qualitative data types that interact with the system.

2.6.4 Lack of Qualitative Reasoning Mechanisms

Current approaches are dependence upon quantitative reasoning and determination. With such heavily reliance upon these sources no facility for implementation of qualitative reasoning or implementation of heuristic based information exists as part of current systems. The approaches detailed in Section 2.5 are totally reliant upon quantitative data sources and preclude the ability of qualitative data from operators for localisation adjustments. Such qualitative information can provide adaption to account for localised pan stage operating conditions.

2.6.5 Reactive Approach to Decision Making

Current practices prohibit future forecasting and are more reliant upon reaction to problems. An overview of cane receival, juice processing, pan stage and centrifugal station and the impacts of their processing operations is not available. In particular an overview of their interactions with the pan stage as well as an overall pan stage overview is recognised as greatly assisting pan stage operator decisions (Yu and Broadfoot, 2001; Dodd, Yu, Broadfoot and Chiou, 2002).

The intuitive forecasts that the operators carry out are relatively short term and their accuracy is also subject to experience and training. Due to the complexity of pan stage operations, the wide range of processing tasks, monitoring of activities and co-competing objectives it would be beneficial for operators to have assistance in determining optimal decision strategies through a supervisory support system utilizing look ahead mechanisms with predictive capabilities. This leads to a more structured approach to decision making and aids in long term planning.

2.6.6 Computerized Outcomes without Proper Explanation or Justification

Previous approaches provided no forms of justification or explanation to justify computer based outcomes. This additional information is required as supplementary information to support system outputs.

In order to garner user trust, bolster confidence, improve satisfaction and aid in overall system adoption, system recommendations and advice may not be accepted as the best possible actions. These must be supported by further reasoning based information and made available as part of explanatory procedures (Gregor, 2001; Gregor and Yu, 2001).

2.6.7 Overly Large Scale Application

Traditional methods of mass balances type schemes for factory and pan stage process provide material quantification on an overly large scale. These large scale generic models quantify process material rates and characteristics with limited focus on internal pan stage workings through a black box style of modelling which models the major input and output material flows of the overall pan stage.

Such approaches also suffer from lack of forecast ability. These models are essentially steady state flow systems predicting only long term average production. Results from such an approach are not able to be localised or able to reflect instantaneous flows at any given point in the overall pan stage schedule. No timescale mechanism is available as part of these approaches to aid in prediction or forecasting.

2.7 Requirements for Decision Support in Pan Stage Operations

In this thesis a KBSSS framework based on the fuzzy system approach will be proposed to integrate several supporting intelligent software technologies. This integration is to facilitate the provision of expert advice for application to pan stage best practices and management within the industrial setting of a sugar mill. A proposal for the KBSSS framework will be presented in Chapter 3 which follows.

However before proceeding with the proposal of the KBSSS, that will be applied specifically for the pan stage environment, it is important that several of the shortcomings identified within Chapter 2 be overcome. The primary requirements of the proposed KBSSS framework should be capable of:

1. Fulfilment of pan stage control and management objectives;
2. Seamless integration of system components;
3. Heuristic inference;
4. Pre-emptive and predictive problem solving capabilities; and
5. Descriptive recommendations with explanatory facility.

2.7.1 Fulfilment of Pan Stage Control and Management Objectives

The system recommendations, prediction of future pan stage operating conditions and advice justifications that the pan stage operators receive from the KBSSS should:

1. Result in a formal structure to the decision making procedure and reduce the number of ad hoc decisions and, consequently, the number of incorrect and suboptimal decisions;
2. Achieve increased productivity with the existing equipment, by employing strategies that are recommended by the KBSSS;
3. Make improved use of the equipment capabilities to achieve sugar recovery, sugar quality and steam consumption targets while fulfilling the production rate requirements; and
4. Forewarn of potential problems with the current operating strategies.

As identified in previous literature (Yu and Broadfoot, 2001), in order to achieve these objectives the KBSSS is required to use the following information in its determination:

1. Projected cane crushing conditions and calculation of syrup input to the pan stage;
2. Projected production loading on the different pan stage operations;

3. Status of each pan, buffer storage tank and product receiver - accounting for the stage in production cycle or level of equipment;
4. Operating status of the centrifugal station;
5. Serviceability of all equipment items;
6. Minimum cycle times for each pan for current operating circumstances; and
7. Steam consumption requirements for the individual pans to meet different target production rates.

Cogeneration is of emerging importance to the Australian sugar industry. In the future energy efficient operation of pan stages will be an important processing objective. The steam consumption of each pan depends upon a large number of factors over which the operator often has little knowledge or control. Identified factors (Miller, 1988) which determine the consumption rates include:

1. Concentration of feed streams;
2. Concentration of pan contents;
3. Heating steam pressure;
4. Operating vacuum and temperatures;
5. Current crystal size and percentage of crystal;
6. Level of material in the pans;
7. Inherent crystallisation characteristics of the material;
8. Operator intervention including mistakes and errors of judgement; and
9. Equipment failure ranging from minor nuisances to major breakdowns.

These factors influence the steam consumption rates of vacuum pans. Minimisation of steam usage is critical for the cogeneration of electricity and the knowledge based supervisory support system is to be developed to schedule assist in the determination of efficient steam usage.

The knowledge based supervisory support system must also handle the processing objectives of pan and fugal stations. These are to:

1. achieve the required processing throughput;
2. maximise yield; and
3. produce shipment raw sugar of high quality within the nominated marketing specifications.

2.7.2 Seamless Integration of System Components

The pan stage is recognised as the most complex section of factory operations (Sugar Research Institute, 2001). There is considerable process interaction between the pan stage and centrifugal stage although management of the centrifugals is undertaken by different operators. The overall strategic management of the pan stage is quite difficult because of the very large number of process streams of varying compositions and crystal growth rate characteristics which must be managed (Miller and Broadfoot, 1997). Often the pan stage is managed in a sub-optimal manner because an overview of operations encompassing various sections of the sugar factory - cane receival section, juice processing stations, the pan stage and centrifugal station - is not available. This limitation has been identified as one of the major shortcomings for current pan stage operations.

In the provision of facilities to provide an overview of the various section it is required that a wide variety of information sources from not only these sections of the sugar factory are integrated but also information sources ranging from pan stage operators, heuristic based rules and developed industrial process models relating the pan stage and its interaction with the overall sugar factory. These information sources are further detailed in Chapter 3.

A melding of system components allows the collective capabilities of each component to act cooperatively resulting in a significantly more powerful and effective inter-system interactions while reducing the limitations of an individual component acting on a stand alone basis. Such hybrid systems generally involve multiple individual artificial intelligence technologies that are either used in series or integrated in a way as to produce advantageous results through synergistic interactions (Lin and George Lee, 1996; Tsoukala and Uhrig, 1997).

2.7.3 Heuristic Inference

The system should have the capability of operating with both algorithmic dependant data as well as heuristic rules. The dynamic interrelation models for the pan stage operations are numerical in nature while the expert system is linguistic. These are described further in Chapter 3. Heuristic capabilities allows informal knowledge to be included as part of the inference process. This allows qualitative data types and heuristic based information to be modelled and integrated as part of system knowledge.

Although fuzzy logic provides the benefits of resilience, robustness, capabilities to work in presence of missing rules and the ability to handle uncertain, vague and imprecise information it is not able to function on missing or arbitrarily noisy data (Cox, 1995; Berkan and Trubatch, 1997; Cox, 1999). The system also needs to be able to handle unreliable and missing data along with localised information provided as part of heuristic based rules.

2.7.4 Pre-emptive and Predictive Problem Solving Capabilities

Predictive problem solving capabilities will allow forecasting of potential future problems, and allows operators to take precautions before problems occur (Dodd, Broadfoot, Yu and Chiou, 2005b; Dodd, Broadfoot, Chiou and Yu, 2008b). In the context of pan stage operations, predictive models for pan stage processes based upon a time scale basis can be used to monitor and predict future operating conditions of the pan stage to take preventative measure and help avoid unwanted scenarios.

Such a pre-emptive approach to pan stage control and management, when working towards the previously presented goals for pan stage control and management, can help to provide preventative measures and aid in best practices by helping to improve remedial actions and provide assistance in selection of control strategies.

2.7.5 Descriptive Recommendations with Explanatory Capabilities

Previous research (Johnson and Ye, 1995; Gregor and Benbasat, 1999; Gregor, 2001; Gregor and Yu, 2001) has showcased the need for expert system recommendations to be further accompanied by explanations to aid in the understanding and justification of presented advices. Realised benefits include increased user acceptance and confidence with improved system adoption outcomes.

A user-friendly supervisory support system interface for the pan stage operations is recognised as being beneficial in assisting these personnel to perform their task more effectively (Yu and Broadfoot, 2001). Since the KBSSS is to provide technical information on which decisions should be based, it is mandatory that its output, advices and recommendations are accompanied with an explanation to assist the user to understand the underlying rationale. In some circumstances, the end user may see an offered advice or recommendation as not being the best available solution. The system needs to be able to justify its outcome in assisting users in making critical decisions.

2.8 Limitations and Scope of the Research

Due to the scope of the research, the thesis is limited to the following areas: The limitations of this research project are highly dependent on one another and can be summarized as follows:

- **Scope.** This research project is specifically focused on the development of a hybrid fuzzy logic expert system, integrating the three define innovative software technologies previously defined. The project is limited to application on the pan stage in a sugar mill and the development of a prototype system showcasing the viability of the research approach. The software implementation is limited to only featuring the selected innovative supporting technologies discussed in this thesis.

- **Limited funding, time and resource constraints.** The main limitation is that the research has to be carried out in the PhD degree timeframe. A major portion of the research involves the design and implementation of a hybrid fuzzy logic expert system and as such the major resources needed are computer hardware and a software development environment. Software systems are heavily reliant upon computer processing power and memory. The computer hardware provided for the research was a parameter that must be worked within. Software development was undertaken using a modern integrated development environment and backend databases were constructed to store information under an industry standard RDBMS database server.

- **Empirical based modelling approach.** Stock tank and vacuum pan feed rate models are based upon an empirical approach. Models for prediction of sucrose and impurity loadings to the pan stage also use an empirical modelling method for their derivation.

- **Test data.** Test data is restricted to the information provided by Racecourse sugar mill during the September 2003 period of the crushing season. The availability of specific control system data also provides a fundamental basis for the sugar mill control system information data sources used to interface with the developed KBSSS. The availability of specific data from the sugar mill control system helped form a boundary on the development of the pan stage process models and their associated implementation in the prototype system. This is due to the need to work within the constraints of available information.

- **Prototype.** Given the timeframe, basis for the device and testing the concept by developing a benchmark prototype, only a prototype of the knowledge based supervisory support system will be developed. It is envisaged that commercialisation of the developed knowledge based supervisory support system would take place as part of follow-on research.

- **Results.** Although outcomes generated as a result of the research may be able to be generalized to other case studies and implementations at other sugar mills, the specific results presented in this thesis pertain to direct outcomes at Racecourse sugar mill pan stage.

- **System advice and recommendations.** Provision of advice is for standard pan stage operations. The prototype system is not developed to offer advice in situations of equipment failures, interruptions or circumstances leading to excessive delays and deviation from the standard pan stage schedule or the A, B, C massecuite boiling arrangement that is common to Australian sugar factories. Other similar circumstances would include the commencement of crushing during the start of season or factory closure at end of season typically where there are specialized procedures for the building or depletion of process material stock tank levels.

It is envisaged that further research and development would be undertaken as part of a follow-on project to incorporate the provision of such advice under these scenarios. Advice under these and other non-listed but uncommon circumstances is not within the scope of the prototype KBSSS.

2.9 Summary

This chapter has provided the background on the problem of pan stage control and management within a sugar factory environment and provided an overview of the sugar production and pan stage processes. It has reviewed the attempts, and their subsequent limitations, made in order to provide a knowledge transfer for better support and management for the sugar mill pan stage setting. The role of decision support pertaining to pan stage operations has been assessed and its critical limitations identified. Considerations for specific requirements have been proposed that may assist in overcoming these limitations. The limitations and scope of the research have also been outlined.

Based upon the requirements presented in this chapter, the details of the proposed knowledge based supervisory support system framework will be described in the following chapter. A brief description will also be provided of the three core innovative supporting technologies that will be employed to support the functionality of the proposed framework. These three supporting technologies are the dynamic industrial process models describing the pan stage process inner workings and the pan stage interaction with other sections of the sugar factory, integration of the process model within the fuzzy expert system rule base and supporting explanatory capabilities for offered system advice and recommendations.

Chapter 3: Proposal for a Knowledge Based Supervisory Support System Framework

3.1 Introduction

In the previous chapter, critical limitations for approaches undertaken to assist in pan stage decision support were identified and requirements for overcoming these were suggested. These factors will help form the fundamental basis for a knowledge based supervisory support system for pan stage operations. In this chapter, a knowledge based supervisory support system framework will be proposed for the pan stage best practices and management which will build upon the identified factors from Chapter 2. A review of the commonly accepted fuzzy logic based expert system framework will be undertaken and extended in order to mitigate previously identified limitations and address the additional system requirements. These extensions will include the incorporation of dynamic industrial process models relating the fundamental features of the pan stage and its interaction with the sugar mill, integration mechanisms to merge these models within the expert system rule base and explanatory capabilities for justification of system advice and recommendations.

This chapter is organised as follows. Section 3.2 provides the premise and rationale for a KBSSS. Section 3.3 details the proposed KBSSS framework. Section 3.4 details the layered component architecture that the framework adheres to. The final sections outlines the innovative features that support the KBSSS, namely: dynamic industrial pan stage process models in Section 3.5, integration of pan stage process models into a fuzzy expert system rule base in Section 3.6 and explanatory capabilities using discourse semantics in Section 3.7.

3.2 Premise for a Knowledge Based Supervisory Support System Framework

As reviewed in Chapter 2, there are specific requirements for decision support for the pan stage. The higher overall goal is to develop a framework that can be integrated within the existing sugar factory industrial environment and work cooperatively with existing infrastructure and factory support personnel in order to affect improved best practices and management strategies for pan stage operations. Also reviewed in Chapter 2, the sugar industry's eagerness to innovate is a result of the very real pressures that exist on the industry as a whole along with the relatively low existing world sugar prices. The industry has responded to such pressure through developing innovative solutions to reduce costs and boost revenues. This provides the rationale for the proposal of a KBSSS and forms the foundation for a hybrid fuzzy logic based expert system that is based upon existing pan stage practices and further enhanced through the provision of intelligent system technologies (Dodd, Broadfoot, Yu and Chiou, 2005a; Dodd, Broadfoot, Yu and Chiou, 2008).

The KBSSS is fundamentally a hybrid fuzzy logic based expert system incorporating fuzzy logic, dynamic interrelational process models of the crystallisation stage and explanatory capabilities. The expert system knowledge base is primarily composed of human operator knowledge of factory procedures and best practices coupled with the dynamic interrelational industrial process models that describe future pan stage operating conditions.

3.3 Proposed Framework

The KBSSS works in tandem with the pan stage operator and current pan stage computer control systems to perform the requirements specified in Chapter 2.

Figure 3 provides a visual depiction of interactions between the current systems and the operator. Existing pan stage infrastructure consists of sugar mill control system that interfaces directly with, and controls the pan stage operations. A pan stage operator interacts directly with this system.

The KBSSS is part of a cooperative control strategy and works in conjunction with the sugar mill control system and pan stage operators. It takes operator input along with information from the existing sugar mill control system via a real time parasitic data feed from the sugar mill control system databases. The KBSSS influences pans stage processes through the actions performed by the operators. The operators use advices/recommendations, in line with the reasoning process from the KBSSS, to influencing pan stage operations through their interaction with the sugar mill control system. Such an arrangement also serves to keep human decision making as part of the process.

The KBSSS uses intelligent system technologies to provide a standardized approach for pan operations by integrating data from a variety of information sources from different sections of the sugar mill, along with dynamic process models of the pan stage and the collective knowledge and expertise of pan stage operators. The innovative KBSSS framework presented in this chapter allows the unification fragmented systems of data. These sources range from pan stage operators, fuzzy rule base, developed industrial process models of the pan stage and information sources across varying sections of the sugar mill to solve an important industrial control problem. Across the sugar mill the KBSSS draws information from cane receival sections, juice processing station, the pan stage, centrifugal station and the pan stage operators as depicted in Figure 3. The mathematical relationships existing between major system process variables and empirically derived relationships from real world knowledge are recognised as being complimentary information sources for real time

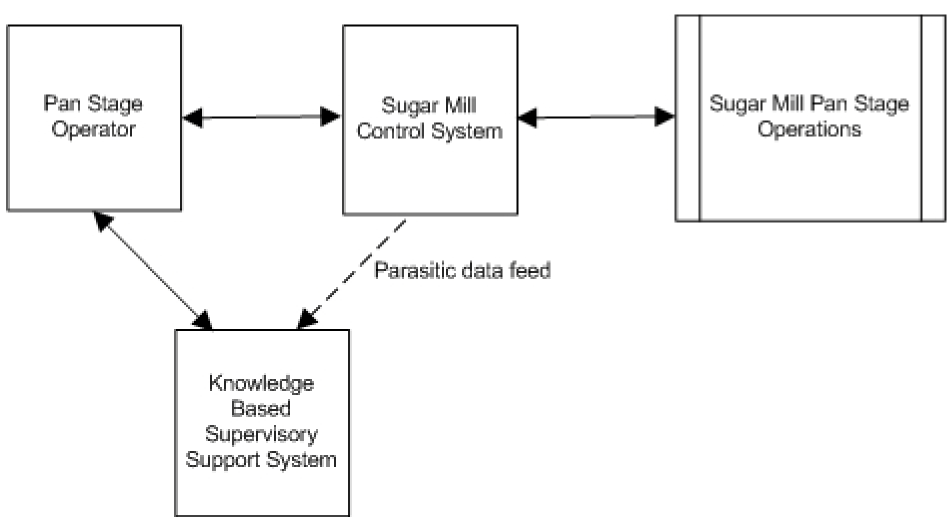

Figure 3: System interaction of the proposed knowledge based supervisory support system

knowledge based systems (Leitch, Kraft and Luntz, 1991).

The integration of the wide variety of information sources along with the requirements and expectations of such a system, as presented in the Chapter 2, leads to a challenge in the design and development of the KBSSS. Previous research (Dodd, Yu, Broadfoot and Chiou, 2002) acknowledges that no conventional software engineering methods exist to provide an overall solution to this industrial problem due to the magnitude of its complexity, the wide variety of information sources required to be managed, overall management objectives, lack of adequate sugar mill crystallisation stage process models and requirements for advisory strategies and supporting advice to validate recommendations. Such wide and varied requirements are not easily managed and no such software based system for their unification currently exists to provide a unified solution.

An innovative modular system architecture based upon a layered system framework is now presented along with major system features. The major features of this framework that are described in the following sections are:

1. Layered component architecture;

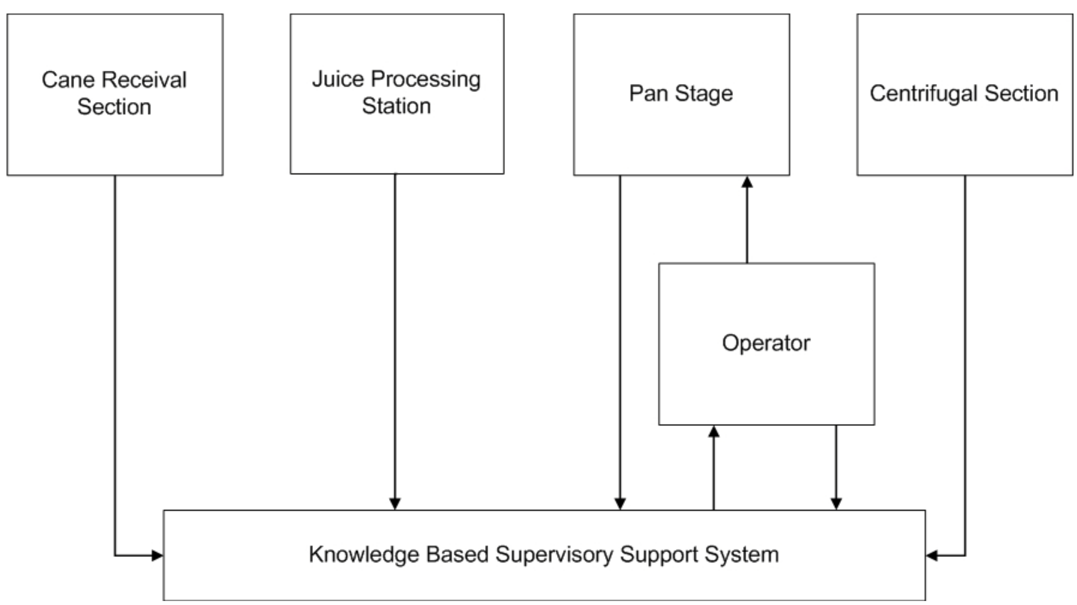

Figure 4: Major sources of input for the proposed KBSSS framework

2. Dynamic interrelational pan stage process models;
3. Integration techniques for merging the dynamic interrelational pan stage process models into a fuzzy rule base; and
4. Explanatory capabilities through discourse semantics.

These features are outlined in the following sections.

3.4 Layered Component Architecture

The overall architecture is layered with components performing layered tasks. The structural partitioning and layering of the hybrid fuzzy logic based system components in the architecture has been identified as key factors in promoting system ownership, security, maintenance, accountability, upgradeability, adaptability and flexibility (Chiou, Yu and Lowry, 2002).

Modular design helps to reduce software complexity, facilitates software maintenance and results in easier implementation by encouraging parallel development of different parts of the system (Pressman, 1997). Such modularity assists in the overall system construction, testing and debugging of the system modules and leads to their independent development allowing parallel system development.

Layering aids in the security of information. Because the pan stage expert system draws on a variety of sugar factory data sources a modular independence ensures data separation with no interference on existing factory information sources or infrastructure. Interactions are also simplified through connectivity to sugar mill information sources occurring through only a single input layer.

3.4.1 Modular System Architecture

The KBSSS modular architecture is based upon conventional expert systems (Leung and Wong, 1990; Gisolfi and Balzano, 1993) and conventional If-Then fuzzy rule based systems design (Goel, Modi, Shrivastava, Chande and Gaiwak, 1995; Berkan and Trubatch, 1997) with substantial extension of the conventional fuzzy knowledge base system framework (Chiou, Yu and Lowry, 2002; Yu, Chiou and Dodd, 2005; Yu, Chiou and Dodd, 2007).

Specialist adaption is also required in order to convert the framework to meet the specific requirements of pan stage decision support (Dodd, Broadfoot, Yu and Chiou, 2008).

The classical fuzzy expert system architecture is presented in Figure 5. This architecture is typically constructed of the following layers:

- **Editor Layer** – Fuzzy variable function editor and If-Then rule editor.
- **Data Layer** – System knowledge base.
- **System Layer** – Fuzzifier, inference engine and defuzzification components.
- **Input layer** – User interface for system inputs.
- **Output layer** – User interface for defuzzified system results.

In order to support the three innovative technologies specified in Section 1.2 modifications to the classical fuzzy expert system architecture have been undertaken. Compared to the conventional fuzzy logic expert system design, as presented in Figure 6, the editor layer is

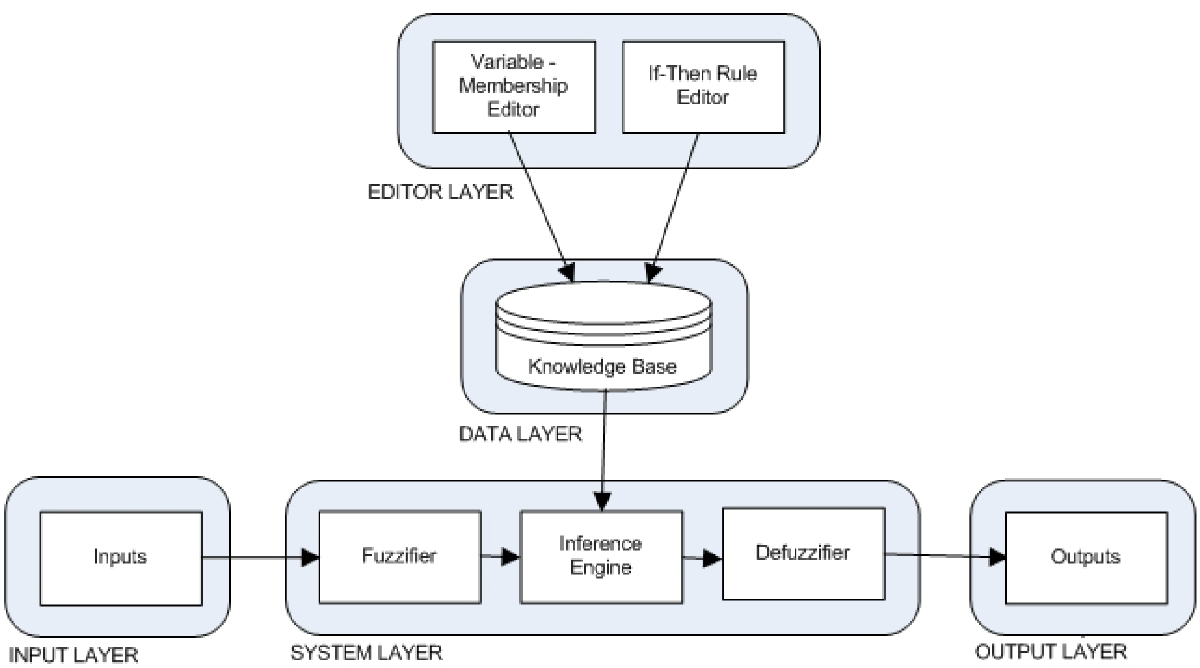

Figure 5: Classical fuzzy expert system architecture

essentially unchanged with only the addition of an editor to customize parameters of the industrial process models of the pan stage. The data layer now also includes the dynamic interrelation models of the crystallisation stage. The defuzzification component that is typical of fuzzy logic expert systems has been replaced by a meta-consequent function (Chiou and Yu, 2007c). The support and real-world layers have also been added. The input and output layers have also been separated. The industrial process models of the pan stage are now tightly integrated with the expert system rule base and work in tandem with the inference process.

Figure 6 provides a simplified representation of the extended system framework. This representation gives a clear comparison to the "standard" fuzzy logic expert system framework that is commonly used and highlights the extensions that have been engineered. The proposed architecture gives rise to the following modified layers:

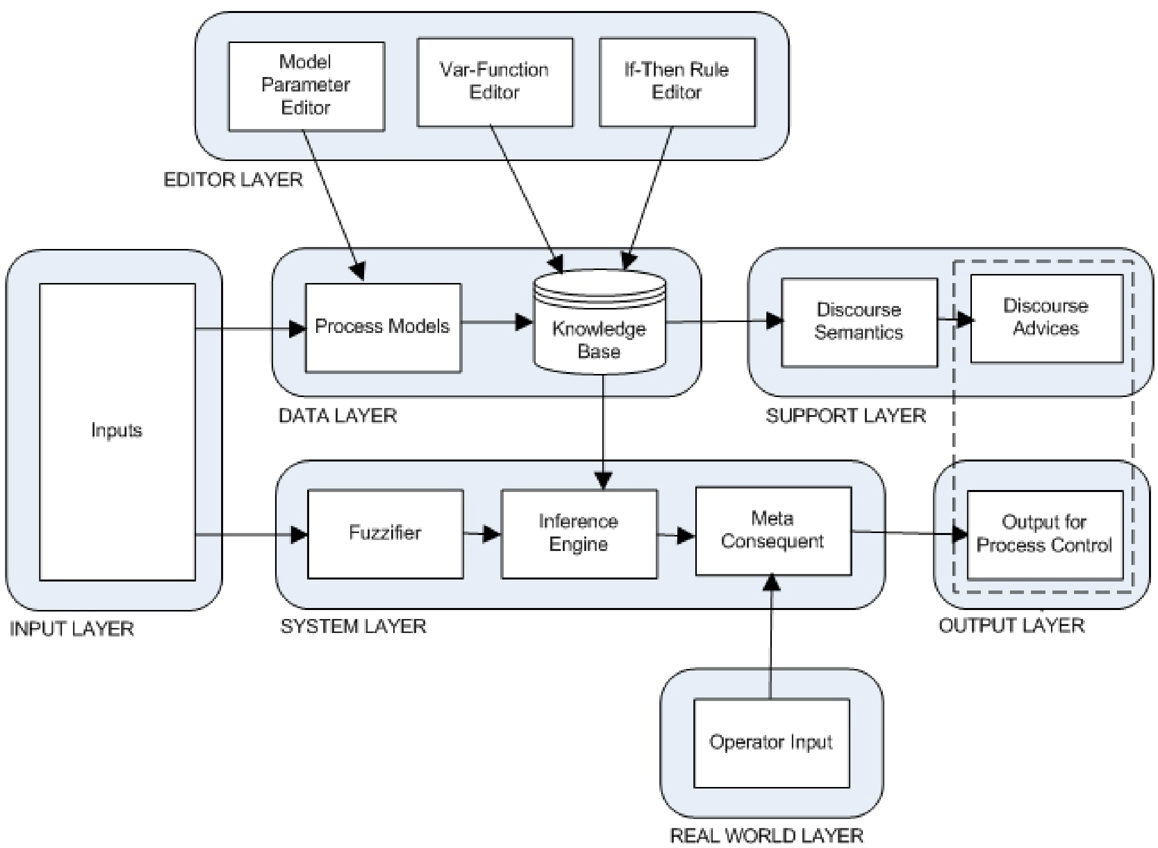

Figure 6: Proposed KBSSS system architecture extended from previous research (Chiou, Yu and Lowry, 2002)

- **Editor Layer** – Fuzzy variable function editor, If-Then rule editor and dynamic pan stage process model parameter editor.
- **Data Layer –** Knowledge base and dynamic interrelational pan stage process model components.
- **System Layer** – Fuzzifier, inference engine and meta-consequent (Chiou and Yu, 2007c) components.
- **Input layer** – Parasitic data link to sugar mill control system information sources and pan stage operator input.
- **Output layer –** Discourse advices and output for process control components.
- **Support layer** – Discourse semantics (Chiou and Yu, 2007a) and discourse explanatory components.
- **Real world layer** – Data from external information sources via user interface component.

As depicted in Figure 6 the KBSSS is a modular architecture with clustered elements performing the layered tasks described. It is important to realise that the discourse semantics (Chiou and Yu, 2007a) and meta-consequent functionality (Chiou and Yu, 2007c) mechanisms presented here are the results of other research for fuzzy logic based expert systems and are specialised components in the extended framework.

3.4.2 Inter-Layer Data Communication

In upholding the previously discussed design principle of the system architecture, the layers are separated and do not communicate directly. This separation allows for error checking of data flows between the layers and data validation. Data is checked for accuracy and for acceptable range and tolerance.

The location of the database storage system used by the KBSSS may not reside with the client application software. The KBSSS draws from database systems native to the software application as well as sugar mill control systems data as presented in Figure 3. Information storage for control system data resides across the sugar mill for the cane receival sections, juice processing station, the pan stage and centrifugal station sections of the factory. The KBSSS draws from information sources for each of these sections. Communication with these information sources is done in a read-only manner to adhere with factory information technology procedures and policy in maintaining the critical control systems information sources.

3.5 Process Models

As described in Chapter 2 the pan stage is a complicated feed-forward and feed-back series of operations superimposed upon a series of batch and continuous processing operations. In order to forward predict future pan stage operating conditions, a sequence of process models to describe the overall process is necessary. A series of models collectively working together to describe the primary inputs and outputs are required along with actual models of the internal workings of the pan stage itself. In order to overcome potential limitations, as identified previously in Chapter 2, these models are required to have the capability of prediction upon a time scale basis. For modelling purposes Figure 7 provides a simplified representation of a sugar mill factory with some factory features, discussed in Section 2.2, merged into the representation for simplification.

Models are required to quantify both the input and output features of the pan stage

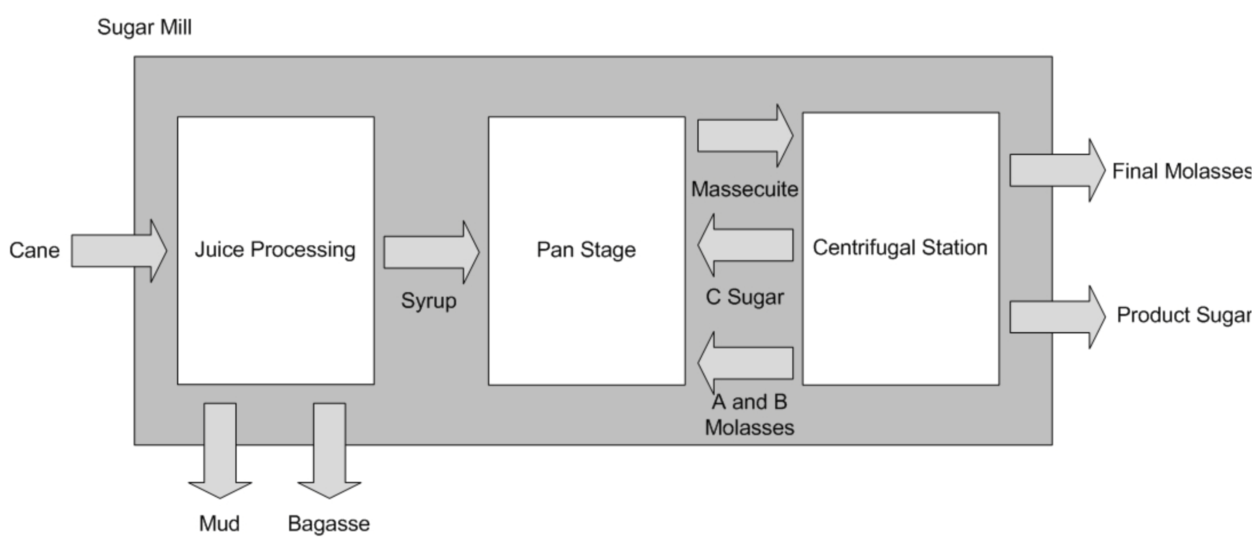

Figure 7: Modelling representation of the major product streams for a sugar factory

processing section of the sugar factory. This equates to establishing relationships for juice processing and the centrifugal station and how they interact with the pan stage. In order to achieve this, models for both the overall juice processing section and the centrifugal station need to be constructed. Output from the juice processing section forms the input to the pan stage. The centrifugal station uses pan stage outputs and also has recycle streams of C sugar and molasses feeds returning to the pan stage.

In order to fulfil the requirements of advice for the KBSSS and in keeping with the objectives and system requirements presented in Chapter 2, a series of models are also required to relate together the internal workings of the pan stage as depicted in Figure 2. In determining pan stage stock tank levels the rates of usage of the feed materials used by the vacuum pans throughout the various phases of their operation are determined empirically and combined with the schedule that the vacuum pans adhere to. This allows a forecast of stock tanks levels when coupled with models determining input quantities occurring as part of the future schedule. This integrated approach also requires the determination of the current phase in the schedule of the vacuum pans and centrifugals for use over the forecast period. The power afforded by empirical knowledge and its specialised role in knowledge based industrial automation systems was discussed in previous research (Leitch, Kraft and Luntz, 1991).

The author proposes to develop and integrate a series of pan stage process models, with supporting intelligent systems techniques as proposed in Section 3.6, for the prediction of future pan stage operating conditions. These models will work together collectively to describe the relationships of the internal pan stage components along with the pan stage interaction with the overall sugar factory.

These interrelational industrial process models collectively describe the dynamic features of the pan stage processes and form a key component of the proposed KBSSS architecture. These models which are further described in Chapter 5 are:

Syrup rate prediction model. Syrup comprises the primary input to the pan stage. This model predicts the future syrup loading quantities to the pan stage by relating cane receival data with juice processing information through use of an empirical factory operational fraction. This measure determines the fractional sucrose and impurity losses through bagasse and mud by-products and consequently the sucrose and impurity quantity loadings to the pan stage;

Steady state steady state flow model. Predicts the long term production rates and flow characteristics for the equipment items on the pan stage and centrifugal station and calculates required footing quantities for seed pans to produce sugar of the required size;

Empirical vacuum pan models. These models quantify the rate at which feed materials are used during each phase of vacuum pan operations;

Vacuum pan phase determination and forecast model. This model provides a status determination of the batch vacuum pans operating status and which potion of the strike they are operating within. A list of expected operational phases the pans will go through during strikes over the forecast period is then dynamically built using the empirical vacuum pan models;

Stock tank prediction models. Models used to predict future stock tank levels of A molasses, B molasses and syrup stock tanks on the pan stage by accounting for feed materials taken from the stock tanks during the pan stage schedule and integrated with expected tank input quantities from juice processing and centrifugal station returns; and

Schedule optimization model. This model provides advise on vacuum pan start and drop times to mesh in with the current operational schedule and provide assistance for vacuum pan steam usage rates and the selection of optimal duties for swing pans.

Individually these models provide information on smaller portions of the overall pan stage. These models are then collectively combined to relate together the various sections of the pan stage along with key features of the internal working status of the pan stage. The innovation of these models is prediction of the following characteristics for the listed equipment items over the forecast period:

1. **Vacuum Pans**

    - expected feed material consumption rates for syrup, A molasses, B molasses and steam throughout the phases of pan duties.

2. **Receivers**

- level;
- holding time till fugalling commences; and
- expected time of pan drop to receivers.

3. **Centrifugals**
   - massecuite fugalling rates from receivers;
   - start and completion times of fugalling;
   - duration of fugalling massecuite from receivers; and
   - molasses production quantity returns to stock tanks.

4. **Stock Tanks**
   - level;
   - expected feed demand quantities; and
   - expected supply quantities.

Prediction of these characteristics allows for forward forecasting of pan stage operating conditions at a future point in the overall schedule. These models work in tandem with the fuzzy rule base described in the next section and also interact via a blackboard system described in the following Chapter 4.

3.6 Integration of Process Models into Fuzzy Rule Base

The interface between the linguistic knowledge base and the numerical mathematical models is built using the fuzzy logic approach. Fuzzy logic and systems techniques are ideal for dealing with hybrid numerical measurements and linguistic operator knowledge data types (Lin and George Lee, 1996), and used to build the expert system knowledge base. The dynamic interrelation models for the pan stage operations are numerical in nature while the expert system is linguistic. The technical challenge lies in the integration of linguistic expressions of human knowledge and dynamic process models which has not been fully addressed in fuzzy systems research (Yu and Broadfoot, 2001).

The overall system architecture is developed in combination with the expert system shell so that "interpretation" of dynamic interrelation models can be integrated with the meta knowledge representation of the expert knowledge base. This incorporation of fuzzy meta-knowledge supports localisation refinement of the fuzzy expert system rules and is an extension of the conventional fuzzy knowledge based framework to include meta consequent functionality (Chiou and Yu, 2007c).

The system knowledge base is static in nature however localised conditions for pan stage processing are not able to be predefined. This warrants adjustment to both model input and output conditions, through the use of fuzzy rules, to account for current operating conditions. These localised operating conditions are not known until system runtime. The real world layer helps provide this additional information to aid in the process of determining how the final defuzzified output is mapped to produce system output.

The author proposes to use fuzzy logic to cater for localisation adjustment due to real world operating conditions. A pre-processing adjustment is to be undertaken for the proposed pan stage industrial process model (as proposed in Section 3.5) input parameters with further adaptation to occur for process model output results. Integration of the dynamic industrial pan stage process models with the fuzzy expert system rule base is needed to relate to the real world operating conditions that exist at system runtime.

The fuzzy rule base is built upon the conventional fuzzy rule based approach with pan stage process models forming a significant component of the knowledge base. These dynamic pan stage process models encapsulate the understanding of segments of the pan stage process and form part of the system knowledge base. These models are chained together through a model hierarchy and used during the inference process.

The fuzzy rules are used in the adaption process to integrate these process models and relate to current operating conditions. This is a core feature in the functionality delivered by the proposed KBSSS and helps to facilitate the localised adaption of model results and customisation of parameters forming model input to match current real world data trends. Pan stage process model outputs are further adapted using fuzzy rules and defuzzified crisp results from this process are fed forward to other process models further down the model hierarchy. Such a scheme allows process model integration with the expert system rule base. An integration scheme is proposed and presented in Chapter 5.

3.7 Explanatory Capabilities (Discourse Semantics)

Previous research (Johnson and Ye, 1995; Gregor and Benbasat, 1999; Gregor, 2001; Gregor and Yu, 2001) has showcased the need for expert system recommendations to be further accompanied by explanations to aid in the understanding and justification of presented advices. Realised benefits include increased user acceptance and confidence with improved system adoption outcomes. The need for such improvements in the field of expert and knowledge based systems has long been recognised (Clancey, 1983; Swartout, 1983; Swartout and Smoliar, 1987; Chandrasekaran, Tanner and Josephson, 1989) with several frameworks presented in attempts to resolve shortcomings.

Specifically, very limited research into explanatory capabilities in the area of fuzzy logic based expert systems has been carried out (Gregor and Yu, 2000) with the need identified for further research into the provision of such enhancements. In recent times some innovation, in area of fuzzy logic based expert systems, has been performed with the development of discourse semantics (Chiou and Yu, 2007a). The discourse semantics approach has been demonstrated through empowering a fuzzy logic based expert system with justification techniques for advice offered in the management and control of parthenium weed.

A user-friendly supervisory control system interface for the pan stage operations is recognised as being beneficial in assisting these personnel to perform their task more effectively (Yu and Broadfoot, 2001). Since the KBSSS is to provide technical information on which decisions should be based, it is mandatory that its output, advices and recommendations are accompanied with an explanation to assist the user to understand the underlying rationale. In some circumstances, the end user may see an offered advice or recommendation as not being the best available solution. The system needs to be able to justify its outcome in assisting users in making critical decisions.

The author proposes a system using textual semantics in tandem with graphical methods in offering explanations to support final system advice. Discourse semantics will be integrated with the fuzzy rule base and process model integration approach, previously proposed in Section 3.6, with results from the pan stage process models displayed graphically.

3.7.1 Discourse Using Textual Semantics

In order to support the primary system outputs, the rationale behind the decision making process should be presented to end users. Justification should be part of the expert systems explanation and is a distinctive process to explanation (Wick and Slagle, 1989b). Supplementary knowledge is needed to explain rules (Wick and Slagle, 1989a) as the system rule base is built upon expert knowledge but the reasoning behind the importance of these rules is not encoded into standard expert systems. Traditional methods such as trace-based justification and information tagging for standard expert systems have application to be extended to the fuzzy expert system framework.

3.7.2 Discourse Using Graphical Methods

Aside from English based textual justification, justification for recommendation can be provided as a series of graphs or measures to show data trends on the pan stage schedule, productivity and feed material usage. Results on forward prediction of future pan stage conditions can be presented showing the results of current pan stage operations and assist in further explanation on how the system recommendations can provide improvements to aid in better management of the pan stage under current operating conditions.

3.8 Summary

This chapter has outlined a proposed knowledge based supervisory support system framework for pan stage operations. This framework has introduced several innovative supporting technologies to resolve the limitations identified in Chapter 2. The overall framework has been based upon the standard design approach for conventional fuzzy logic based expert systems with extension to include dynamic industrial process models describing the pan stage and its internal features, integration of these process models within the expert system rule base and explanatory capabilities to support system recommendations.

In the following chapter, the overall application design and structure for the proposed framework will be presented. This application is based upon the specifications and requirements for the provision of expert advice in pan stage management and control. The major features of software layers are outlined and the overall software structure is presented. A blackboard system architecture that will be utilized in support of the integration of the intelligent system software components within the knowledge based supervisory support system will also be reviewed.

Chapter 4: Overall Application Design and Structure

4.1 Introduction

The previous chapter outlined a proposal for a knowledge based supervisory support system. The fundamental features of a framework to support the complex issues within the pan stage section of a sugar mill in providing cooperative decision support were presented. The framework is used as a fundamental foundation for the design and implementation of a software system in the provision of such support. This chapter details a software application design and structure which adheres to the software framework presented in Chapter 3. The following sections present the specifications and requirements for the key control strategies in best practices and management of pan stage operations within a sugar mill industrial environment. This is followed by a review of blackboard system architecture detailing how the major subsystem components are integrated within the software system.

This chapter is organised as follows. Section 4.2 outlines the specifications and requirements in the design and implementation of the application. Section 4.3 details the overall application design and the specific features of the layers in the design in adhering to the decision support system framework. Section 4.4 reviews the blackboard system technology that is used to support the integration of the major intelligent system software subsystems within the application. Section 4.5 describes the software structure and how it fits into the overall application framework.

4.2 Specifications and Requirements of the Application

Chapter 2 reviewed the complex issues surrounding the management of the pan stage within the sugar mill industrial setting. Due to the constraints of resources limitations in the availability of experts in the area, the provision and adoption of a decision support system modelling such experts has been proposed.

The system specifications for key KBSSS features require that the system recommendations and expert advice provide four core control strategies (Yu and Broadfoot, 2001). Additionally, the final system recommendations provided by the KBSSS should be supported through the justification and explanation facilities in order to provide the rationale behind the recommended outcomes. The KBSSS implements this by supplying explanatory capabilities and a prediction of pan stage operating conditions over a forecast period. This prediction helps to identify proactive measures and more optimal management strategies by maintaining a forward look ahead mechanism to assist pan stage operators in identifying potential problems and limitations of the current decision making process. Even though the capability to provide a forecast of pan stage operating conditions is formally specified as a supporting component of the KBSSS, its role helps dictate the core control strategies for improving pan stage decision making.

The four core control strategies for the primary system output are:

1. Pan duty management;
2. Pan control strategy;
3. Pan schedule management; and
4. Stock tank management.

Additionally, these core control strategies are supported by a further two secondary system outputs:

5. Prediction of future pan stage operating conditions for given current operational conditions and operating environment; and
6. Explanatory and justification capabilities.

These secondary outputs are critical in providing reasoning and justifications for the recommended system advices. The following sections detail how the overall application integrates several innovative supporting technologies via subsystems to achieve these defined strategies.

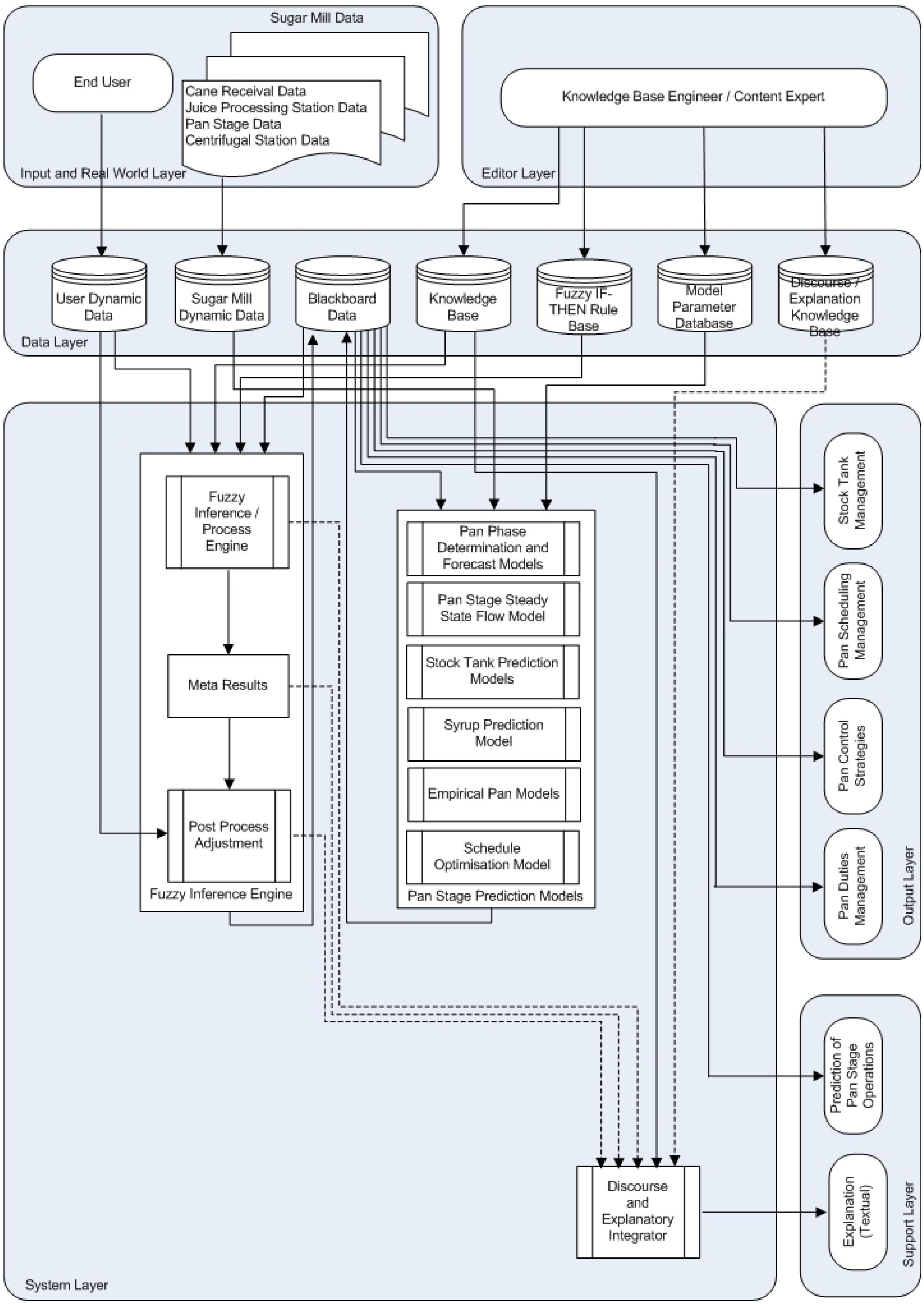

Figure 8: Detailed application design extended from previous research (Chiou and Yu, 2007b)

4.3 The Overall Application Design

The KBSSS utilizes three key subsystems to carry out data processing of the two major sources of system input. These are transformed into the six required system outputs. The subsystems perform the following tasks:

1. dynamic interrelational process models of the pan stage allowing a prediction of future pan stage operating conditions;
2. fuzzy inference engine with fuzzy localisation adjustments to match for real world operating conditions; and
3. explanatory and justification facilities.

Figure 8 displays the modular architecture of the application design. The design architecture is modular with clustered elements performing layered tasks. This architecture is based upon the framework proposed in Chapter 3. The application framework is adapted from previous research (Chiou and Yu, 2007b) but with modifications for supervisory decision support in pan stage operations. Further extension was made in order to integrate the dynamic interrelational process models of the pan stage with the fuzzy rule base. Associated changes also include an innovative blackboard system that functions as both a working memory for data exchange between the fuzzy inference engine and industrial pan stage process models. Also incorporated were facilities for both parameter storage and parameter tuning of the dynamic pan stage process models.

The overall application design includes seven layers – input layer, real world layer, editor layer, data layer, system layer, support and output layers. A detailed description of these layers in covered in the following sections. These layers and their associated functions adhere to that of the proposed layered component framework presented in Figure 6 of Chapter 3 with similarly specified functionality. These layers and their major features are presented in the following subsections.

4.3.1 Input Layer and Real World Layer

The input layer draws data from the cane receival, juice processing, pan stage and centrifugal station sections of the sugar mill via a parasitic data feed from the mills computer based control system. Information is provided in a standard RDBMS format with information updated in real time. Access is provided in read-only mode to prevent modification or interference with data.

Further information from the crystallisation stage operators, through the graphical user interface, can be provided to assist in determination of equipment performance ratings and operational problems and characteristics of the syrup, molasses and sugar process streams along with crushing season information. This information is accepted by the KBSSS through the input layer. Although the real world and input layer, from the framework presented in Chapter 3, are shown in Figure 8 in a merged format, it is important to realise that each has separate input sources which do not interact or conflict with each other. These sources remain isolated.

The importance of a relatively good the user interface for expert systems was highlighted by (Hendler, 1988; Payne and McAurthur, 1990). Since the system interaction is carried out though the user interface, a well designed and easy to use system can help support system adoption. A variety of interfaces are possible given the various systems users. These may be shift supervisor, pan stage operator, knowledge engineer or content expert. Each user has specific system requirements and differing tasks required to be performed. The provided interface view is customised to the type of end user interacting with the system and provides different functionality depending upon operational tasks expected to be performed within the software system and classification duties of the current end user.

4.3.2 Editor Layer

The editor layer provides facilities for specialized users interacting with the system with abilities to perform knowledge development and fine-tuning of KBSSS subsystems. This allows adaption of knowledge/If-Then rule base, explanatory/discourse base and pan stage process model parameter databases. These changes are undertaken by knowledge engineers, content experts and pan stage process experts with specialised domain knowledge and understanding pertaining to each of the major KBSSS subsystems.

This layer provides the knowledge engineer and content expert with the capabilities to modify the fuzzy membership function parameters and fuzzy rules associated with the dynamic process models and to assign or modify the explanations tagged to each of the rules. Facilities for the pan stage expert to tune the default process model parameters that are associated with each pan stage process model are also provided.

4.3.3 Data Layer

The data layer consists of a series of databases for information storage. All databases use a standard RDBMS for interoperability and system interfacing. The final membership functions and fuzzy If-Then rule base are stored in the knowledge base at the data layer along with parameters specific to the industrial pan stage models and discourse knowledge bases. The data layer also includes an innovative blackboard system that acts as a dynamic storage repository for results from the dynamic interrelational models of the pan stage. The blackboard system stores all major results for each future time interval prediction of process model variables. Sugar mill control system data containing information from cane receival, juice processing station, the pan stage and the centrifugal station is also stored. Dynamic user input from the pan stage operator is also captured for later use.

4.3.4 System Layer

The system layer is the most complex of the layers in the KBSSS architecture and essentially comprising the majority of system software operations. These three innovative modules utilize multithreading for each subsystem. Each module runs as part of a separate thread to ensure system execution will continue even under the event of a subsystem failure. These core subsystems as shown in Figure 8 are:

1. Dynamic interrelational process models of the pan stage for prediction of future pan stage operating conditions;

2. Inference engine delivering fuzzy meta results; and

3. Explanatory and justification facilities.

The interrelational process models developed to describe the dynamic features of the pan stage process and provide a forecast of future pan stage operating conditions and forms one of the key subsystems in this layer. The development and mechanics of these models are described in previous research by the author (Dodd, Broadfoot, Yu and Chiou, 2005a; Dodd, Broadfoot, Yu and Chiou, 2005b; Dodd, Broadfoot, Chiou and Yu, 2008b). A basic overview of these models was provided in Section 3.5 of Chapter 3. The major features and implementation details for each of these models will be presented the next chapter, Chapter 5. These models, restated for convenience, are:

1. Pan and fugal phase determination models;
2. Syrup prediction model;
3. Steady state pan stage pan stage flow model;
4. Empirical vacuum pan models;
5. Stock tank prediction models; and
6. Schedule optimization model.

This subsystem provides a prediction of future pan stage operating conditions under current operations. The development and major functions of these models along with some specific results were presented by the author in literature (Dodd, Broadfoot, Yu and Chiou, 2005a; Dodd, Broadfoot, Yu and Chiou, 2005b; Dodd, Broadfoot, Chiou and Yu, 2008b).

The fuzzy inference engine is another core subsystem in the system layer. The meta-consequent component in this subsystem replaces the defuzzier found in traditional fuzzy logic based expert systems and instead of providing defuzzified results it produces meta-results through the use of fuzzy meta-consequent functionality (Chiou and Yu, 2007c). The meta-consequent functionality provides an adjustment to the results of the inference process. It modifies the dynamic pan stage process models output to correlate with information provided by the pan stage operators through the input layer and matches rules from the fuzzy rule base to localised operating conditions.

This subsystem is complimented by information from the real world layer to provide a method for mapping information on equipment performance ratings, operational problems and characteristics of the syrup, molasses and sugar process streams to the dynamic process models. This provides meaningful interpretation of the inference process output by matching it to the operating conditions at the crystallisation stage. The inference engine subsystem involving meta-consequent functions works in tandem with dynamic interrelational process models of the pan stage to determine the primary system output control strategies.

These outputs are further justified by the explanatory subsystem which provides system explanation of final control strategies. Explanations tagged to each rule in the If-Then fuzzy rule base are triggered and propagate through the inference mechanism upon a rule firing. This information is further passed to the support layer for further processing, as discussed in the following section.

4.3.5 Support and Output Layers

On completion of the system layer processes, the final results are passed to the output and support layers. The four primary control strategy recommendations are passed to the output layer for formatting. The secondary supporting results are passed to the support layer for formatting and display.

The support layer works to consolidate the inference process by formatting justifications for the presented advice in the most appropriate format. The method of presentation is an integral part of the output layer. The justification process is independent of the inference process which provides the final control output values as a part of the system recommendations.

Aside from English based textual justification, justification for recommendation can be provided as a series of graphs or measures to show data trends on the pan stage schedule, productivity and steam rate usage. These can be presented against forward predictions of current pan stage operations and provide assistance is highlighting how the system recommendations can provide improvements to the current process.

The method of presentation is an important part of acceptance of final system recommendations. Since the KBSSS is a rather complex software system the overall end user acceptance of system recommendations and advices lies in their structuring and presentation. In a similar fashion to the support and input layers, a variety of interfaces are possible given the varying requirements systems users. These may be shift supervisor, pan stage operator, knowledge engineer or content expert. Each interface view is customised to the type of end user interacting with the system and provides different functionality depending upon the commitments and responsibilities that the user has as part of their personnel duties on the pan stage.

4.4 A Review: Blackboard Systems Structure

As mentioned previously, the knowledge based supervisory support system is designed, in accordance with the structured design framework presented in Chapter 3. An integration type system is required to aid in the merger of the major subsystems, presented in Figure 8. This system is required to manage the different information sources that result from subsystem processing. These subsystems each implement different intelligent systems technologies.

A blackboard system is used to facilitate this information. The subsystems share the results of their specific processing activities through a common information repository know as a blackboard which is responsible for the overall feature integration and allows subsystems of differing technologies to communicate via an intermediary storage system.

4.4.1 The Blackboard Model

The blackboard system is an artificial intelligence solution founded on the blackboard architectural-based model. The initial development of the blackboard system approach is synonymous with the Hearsay-II speech understanding system (Erman, Hayes-Roth, Lesser and Raj Reddy, 1980) for which the original approach was developed and consequently showcased as a major artificial intelligence system technology to aid in the solution of complex problems.

The use of a blackboard system is analogous to a team of experts solving a problem. Collectively the team of experts, know as "knowledge sources", work towards an overall problem solution. Due to the individual expertise of knowledge sources they each work on providing solutions to parts of the problem that are specific to their domain. Once an overall specification of the problem has been constructed, each knowledge source interacts with the blackboard when information specific to their domain becomes available. This contribution then allows other knowledge sources the chance to apply themselves. This incremental approach continues with each knowledge source adding portions of the overall problem solution until it is finally solved. A control mechanism is implemented which dictates the order that the knowledge sources may interact with the blackboard system. This establishes an effective and coherent method of interaction in problem solving.

A blackboard system consists of three major components:

1. **Knowledge sources.** Knowledge sources are the expert modules that interact with the blackboard.

2. **Blackboard.** The blackboard is the shared information repository.

3. **Control mechanism.** The control mechanism is the component used for scheduling the reading and writing of knowledge sources to the blackboard. This scheduling is used to organise the knowledge sources interaction with the blackboard in the most effective and coherent manner.

These blackboard model components and their interaction are depicted in Figure 9 with the control mechanism scheduling the overall interactions of the knowledge sources with the blackboard.

The blackboard approach allows diversity in the problem solving approaches able to be used by the knowledge sources, since these sources are totally independent and do not interact. This blackboard system relies upon the need for a common system for interaction between the blackboard and the knowledge sources. Efficient retrieval of blackboard information is also required along with methods for activation of the knowledge sources to provide blackboard updates. The blackboard can be viewed as a shared information repository of partial solutions, suggestions and contributed information that has been provided by knowledge sources.

The blackboard approach is a powerful problem solving architecture allowing diversity amongst knowledge sources, provides a framework for combining fundamentally different knowledge sources and promotes modularity and independence during the design, implementation, testing and maintenance lifecycle phases of the application (Corkill, 1991).

Within this scheme knowledge sources do not communicate directly. This allows great flexibility in the type of knowledge sources and commits to the upgradeability, adaptability, maintenance and flexibility factors mentioned in Section 3.4. Knowledge sources can also be upgraded or modified without affecting the rest of the software. Additional knowledge sources can be incorporated into the overall design easily with no interference to current operations. The only major requirement of these changes is that the final subsystem outputs must still maintain a consistent format for interaction with the blackboard so that knowledge sources may understand the presented results.

Knowledge sources can be treated as black box systems that are diverse in the technologies that they may implement and are particularly powerful and effective for implementation as part of expert systems. Blackboard systems are recognised as a very flexible and powerful system technique for expert systems applications requiring dynamic control decision and applications that combine multiple technologies (Corkill, Gallagher and Johnson, 1987; Corkill, 1991; Carver, 1997; Corkill, 1997). Furthermore, blackboard systems are recognized as having no equal for their powerful combination of capabilities. The benefits of the blackboard approach allows information exchange between knowledge sources that may be fundamentally different and implemented using totally different technologies.

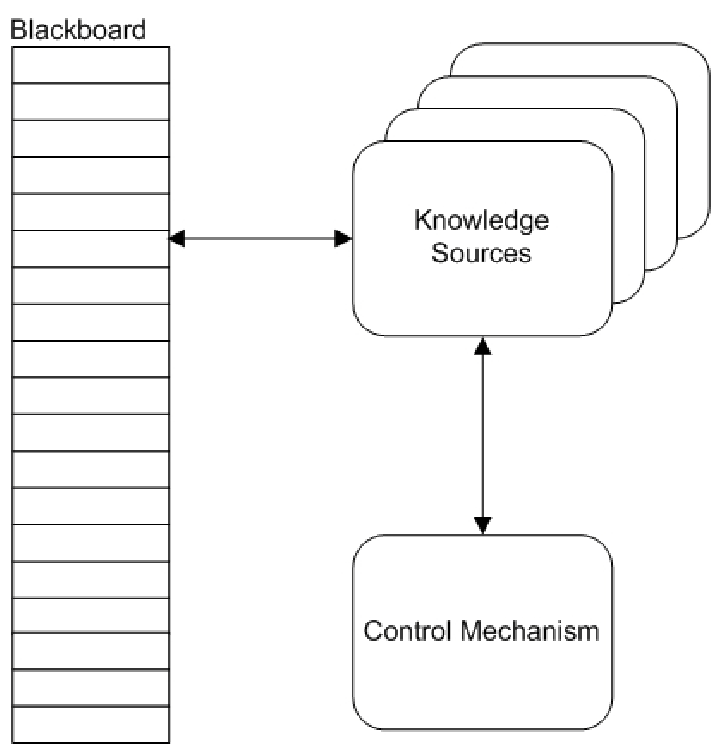

Figure 9: Blackboard system component interaction

Typically knowledge sources inform the blackboard system of blackboard information they are interested in, instead of directly scanning the blackboard itself. When this event occurs the blackboard system considers the activation of such a knowledge source to allow processing. The control mechanism provides this scheduling process and allows knowledge sources to contribute to the blackboard. The control mechanism also ensures all facets of the problem are receiving appropriate attention in development of the overall solution.

Knowledge sources are not restricted to only interfacing with the blackboard information sources. They can also take other system inputs as part of their processing (Corkill, 1997) and function as independent systems. Each knowledge source is recognised as providing specialist services in being able to solve certain portions of the overall problem. The critical requirements for a blackboard system design are the needs for a standardised information storage interface for interacting with the blackboard and an effective and coherent method of scheduling knowledge source interaction with the blackboard.

Blackboard systems are a mature intelligent system technology with techniques available for ensuring their efficiency and flexibility (Corkill, Gallagher and Johnson, 1987) despite the relatively limited publicity and awareness afforded to them, even within the area of intelligent systems (Clancey, 1983). Given the requirements for an integration technique for the varying intelligent system technologies that form the basis for the three subsystems in the KBSSS design, the blackboard model is well suited to allow their integration and provide data exchange abilities.

4.5 Software Structure

The software development was undertaken using a modern integrated development environment and backend relational databases were constructed to store information under an industry standard RDBMS database server. This ensured database interoperability with sugar mill data sources and provides a standardised system storage method.

Extensive use of exception handling throughout the programming phase of implementation aids as precautionary measures in prevention of abnormal system conditions resulting in system failure. Object oriented programming was used throughout design and implementation phases to support the objectives outlined in Section 3.4. Atomic transactions are used for database information processing.

Figure 10 illustrates the overall software structure of the KBSSS implementing the application framework presented in Figure 8. Only system layers pertaining to the subsystem interaction have been presented. The major software subsystems interact via a blackboard system as outlined in the previous section. The overall software structure consists of the following major components: the 3 major subsystems, representing the innovating intelligent system technologies supporting the software application, and a blackboard supporting control mechanism for scheduling the subsystems (as knowledge sources) as detailed in the previous section, Section 4.4.

This control mechanism thread ensures the correct interaction of the subsystems with the blackboard system. Figure 10 also presents the major sources of output occurring as a result of subsystem processing in conjunction with information sources from the data layer. The control mechanism was not previously presented in Figure 8 since it is an ancillary supporting function for use in the management of the execution order of the major application subsystems. The software adheres to scheduling as provided by the master scheduling thread in determining blackboard interactions.

Since the KBSSS acts in a control system supporting fashion, it reruns its entire processing regime at regular predefined intervals to provided updated advice on pan stage best practices and management. In this fashion the entire system work cooperatively and in tandem with existing sugar mill infrastructure as presented in Figure 3 of Section 3.3. User input decides upon overall system termination.

The required execution order of the major subsystems and dynamic industrial process models is due to the data dependencies that exist within information processing and the need for subsystems to access the blackboard, mentioned in the previous section, in an orderly and timely fashion. The series of developed industrial pan stage process models are firmly embedded in the fuzzy logic based expert system rule base. These processes are complimentary with information shared through the blackboard process. This relationship will be further detailed in Chapter 5.

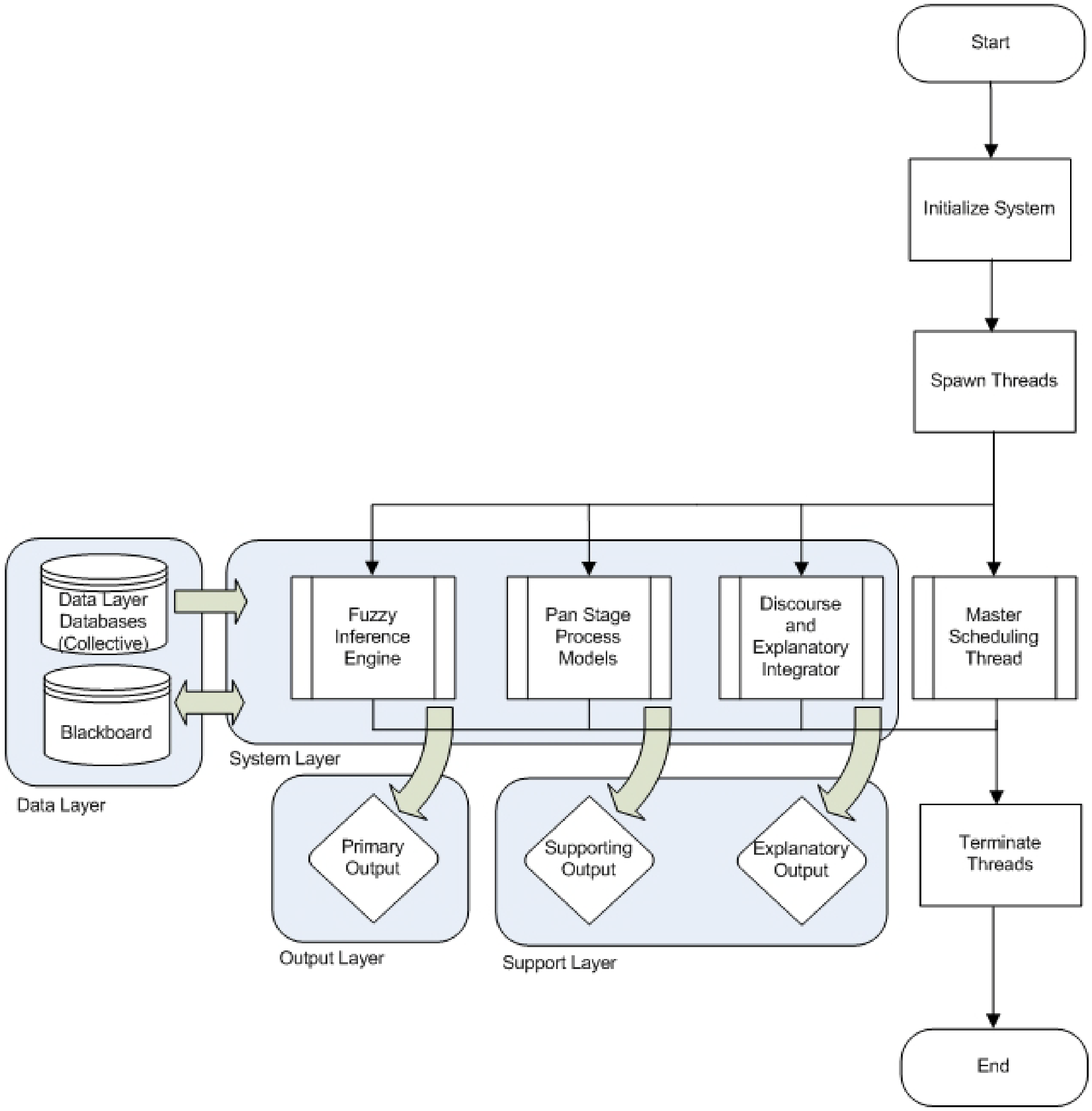

Figure 10: The software structure illustrating system multithreading and subsystem interaction

Due to the need for updating of advice, recommendations and justifications from the KBSSS on a recurring basis, each update interval also requires all user input and databases to be reviewed for updated information. The information sources pertaining to the cane receival, juice processing, pan stage and centrifugal sections of the sugar factory are updated with a live data stream of up to date information during around the clock sugar processing operations.

4.6 Summary

This chapter has demonstrated how the knowledge based supervisory support system is designed, in accordance with the structured design framework presented in Chapter 3. The adoption of this framework leads to the overall application and design as presented. The major features of each layer in the architecture have been detailed.

As the knowledge based supervisory support system is a relatively complex design, the features and integration model for the major subsystems composing the system layer are also presented. The intelligent behaviour of the design is facilitated through the incorporation of three primary intelligent subsystems. The blackboard system architecture for information exchange between the subsystems has been reviewed. The overall design the software structure that the application design adheres to has also been outlined and detailed.

The three primary subsystems were designed to meet the needs of the formal system specifications and requirements. In the next chapter, the method and implementation of the three subsystems which comprise the intelligent core of the overall KBSSS will be presented. These are: 1) Dynamic interrelational process models of the pan stage for prediction of future pan stage operating conditions; 2) Integration techniques for the merger of the dynamic industrial pan stage process models with the fuzzy expert system rule base; and 3) Explanatory capabilities used to justify and support the primary system recommendations and advice.

Chapter 5: KBSSS: Method and Implementation

5.1 Introduction

In the previous chapter, the overall software application and structure of the knowledge based supervisory support system was presented adhering to the adopted framework presented in Chapter 3. The major features of each element in the layered architecture were described, along with the blackboard system structure used to integrate the major subsystems. The software structure of the application was also presented.

This chapter will present the implementation features of the three core innovative supporting technologies for the knowledge based supervisory support system. These technologies are:

1. Dynamic interrelational process models establishing relationships for the internal working of the pan stage and the pan stage interaction within the overall sugar factory process;

2. Integration techniques for merging the dynamic industrial pan stage process models with the fuzzy expert system rule base; and

3. Explanatory capabilities used to justify and support the primary system recommendations and advice.

This chapter is organised into four main sections. Section 5.2 presents the innovative dynamic pans stage process models developed specifically to relate together the segments of the pan stage. Section 5.3 proposes two core system supporting functions utilized as part of the dynamic pan stage interrelational models. Section 5.4 proposes a method for integration of the dynamic pan stage process model within the fuzzy logic expert system rule base to allow prediction of pan stage operating conditions. Section 5.5 details the mechanics of the explanatory capabilities.

5.2 Dynamic Interrelational Pan Stage Process Models

A major challenge in the development of the KBSSS is the development of dynamic interrelational process models of the sugar mill pan stage to relate the various sections together. An overview of the approach was presented in Section 3.5 with a review and limitations of existing modelling approaches presented in Section 2.5.

In order to relate together the sections of the pan stage an innovative modeling approach has been taken. By developing empirical boil-on rate models for each of the vacuum pan feed material streams through the different stages of its strike, the liquor, A molasses and B molasses feed rates for all the pans at a given point in the schedule can be summated given knowledge of the pan stage schedule. This model takes advantage of the repetitive pan stage schedule and consistency in successive pan strikes. A detection mechanism to establish the current point in the vacuum pan strike is also required as part of this approach.

Once the model for each pan is established then the boil-on rates for each feed stream at the different stages of the pan stage schedule can be determined by summing the liquor, A molasses and B molasses feed rates for all the pans at future points in the pan stage schedule.

Given the expected syrup production rate and C sugar remelt production rate to the liquor tank during this interval, the predicted tank levels can be determined for the liquor tank. Similarly the predicted tank levels for the A and B molasses streams can be calculated from the production rates and the molasses return from the centrifugal station and the sum of the consumption rates on the individual pans at a specific point in the pan stage schedule.

Combining projected vacuum pan feed rates into the pan stage schedule with predictions of sucrose and impurity quantities from cane receival data allows forward forecasting to ensure there are sufficient quantities of materials in stock during standard season operation, forewarn of potential problems with the current operating strategies and advise corrective procedures.

Building upon these models, adjustments to the length pan strike times within the pan stage schedule can be undertaken through optimization to aid in the quality of product sugar, improved pan stage recovery, efficient steam rate usage and optimal pan stage productivity. The proposed dynamic process models are integrated and work cooperatively in tandem with the KBSSS expert system rule base framework.

5.2.1 Syrup Prediction Model

The syrup prediction model as formulated in supporting thesis research (Dodd, Broadfoot, Yu and Chiou, 2005a) determines the future flow of syrup to the pan stage for bins of sugar cane entering the factory after the harvesting process. A prediction of the quantities of sucrose and impurities in syrup allows a forward forecasting of the future pan stage loading of syrup. The syrup prediction model uses cane receival data combined with juice processing station information to forward predict syrup quantities and composition. Figure 11 presents the segment of the factory that the syrup prediction model pertains to. This model is of key importance as syrup comprises the basic input to the pan stage with direct feed to the pan stage liquor tank. The liquor tank is considered the first equipment item within the pan stage section.

This model to forward predict the quantity of sucrose and impurities in syrup to the pan stage from quantities of sugar cane was developed as part of sucrose and impurity balances on sugar factory data (Mackay Sugar Cane Association, 2002a; Mackay Sugar Cane Association, 2002b; Fedrick, 2003) provided for Racecourse and Marian sugar mills

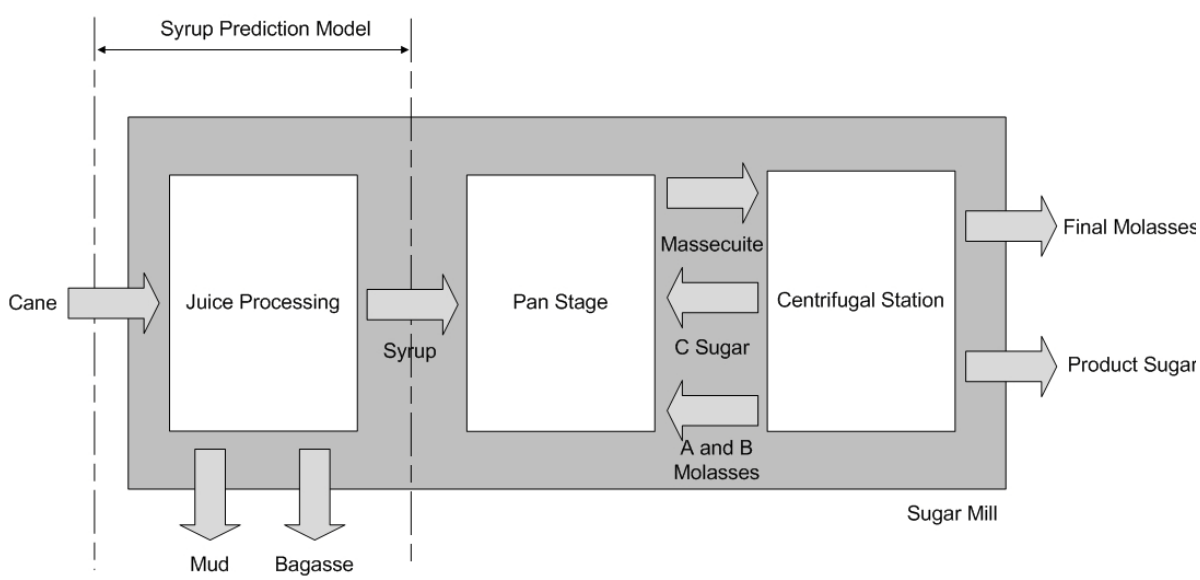

Figure 11: Syrup prediction model in relation to an overall of the sugar mill

(located in Mackay, Queensland, Australia) for 2002 crushing season. Further information on the model derivation is provided in Appendix A.

The derived equation, to predict the future quantity of sucrose in syrup to the pan stage, is presented in Equation (5.1). The relationship for impurities in syrup to the pan stage is presented in Equation (5.2). When summated these models predict the quantity of syrup to the pan stage. This total quantity of syrup is the quantity of solids, taken as the sum of sucrose and impurities, and excludes the quantity of water that is present in practice.

$$s = fqp/100 \tag{5.1}$$

where,

s is quantity of sucrose in syrup to the pan stage (t)

f is an empirical factory operational fraction

q is the quantity of cane crushed (t)

p is pol%cane of crushed cane (%)

$$i = fqp(100-t)/t \tag{5.2}$$

where,

i is quantity of impurities in syrup to the pan stage (t)

q is the quantity of cane crushed (t)

t is purity of syrup to the pan stage (%)

The data required for the model represented by Equation (5.1) and Equation (5.2) are pol%cane, quantity of cane crushed and the purity of the syrup. The purity of syrup corresponding to the cane crushed in a shift (or shifts depending upon sampling methods) will not be available until the lab analysis is performed later in the day. The previous day's information on syrup purity is instead used as an approximation for the current days value.

The empirical factory operational fraction determines the fractional sucrose and impurity losses through bagasse and mud by-products and consequently the sucrose and impurity quantity loadings in syrup to the pan stage. Collectively this determines future syrup quantities loadings to the pan stage and allows a forward forecast of the future pan stage loading of syrup. The relationship of the process material product steams is highlighted in Figure 11 in establishing a relationship from cane to syrup over the juice processing and cane receival sections of the sugar factory.

Given that there is approximately a 96 minute delay from cane entering the factory and being processed to its associated syrup flows to the pan stage, this forms a fundamental boundary on the forward prediction of the overall liquor stock tank prediction model. Further forward prediction beyond this interval relies upon similar syrup production rates being achieved through continued sugar cane crushing rates and factory processing performance.

An innovative dynamic allocation model is proposed in Section 5.3.1 and details how the syrup prediction model is used in order to predict future forecast syrup and impurity quantities to the pan stage based upon cane receival data. This supporting functionality is required in order to implement the proposed models presented in Equation (5.1) and Equation (5.2).

The syrup prediction model in the presented equation format is restricted to only being able to predict quantities. The dynamic allocation algorithm is required to apportion these quantities to future time intervals. This provides the background technology to allow predictions over a forecast horizon. These two systems are tightly bound and work in tandem. This relationship is further detailed in Section 5.3.1.

5.2.2 Pan Stage Steady State Flow Model

The proposed pan stage steady state flow model, as reported by the author in thesis supporting research (Dodd, Broadfoot, Chiou and Yu, 2008a), predicts the long term material flows, and associated purity, for each major equipment item in the pan stage under

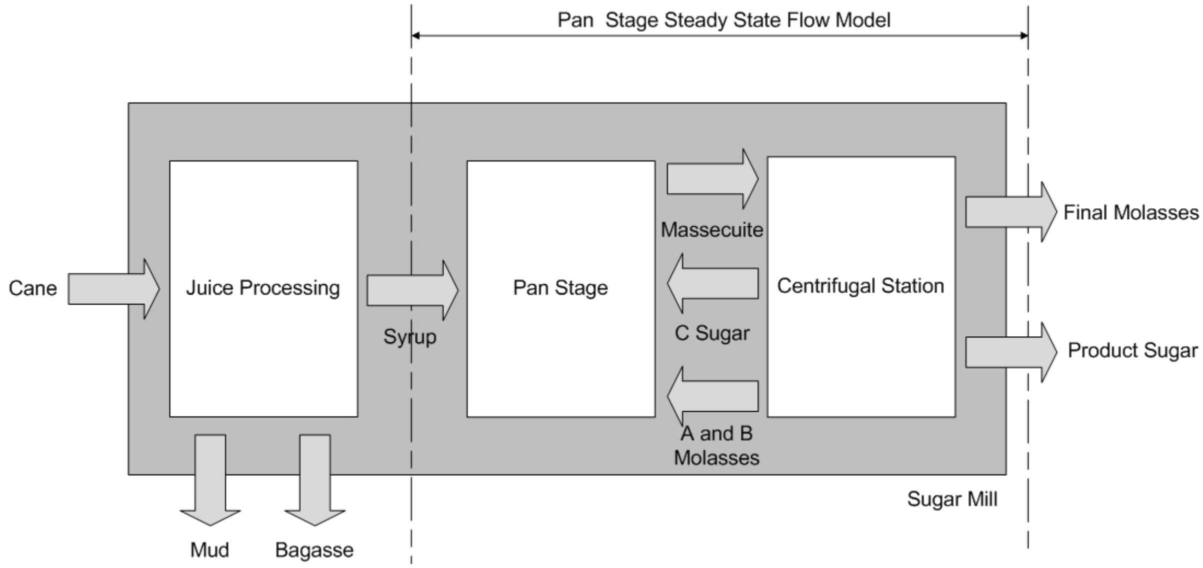

Figure 12: Pan stage steady state flow model in relation to an overall of the sugar mill

the three massecuite boiling scheme that is commonly used for sugar production throughout Australian sugar mills. This pan stage steady state flow model has been developed to calculate the average flow rates and purities of process streams, using mass balances (Bureau of Sugar Experiment Stations, 1984), at each vacuum pan, fugal, massecuite receiver, tank, sugar screw and bin. The model determines the average production rates of massecuite, C sugar remelt, molasses and sugar streams given inputs of the syrup flow rate and purity to the pan stage.

As presented in Figure 12, this model relates the pan stage with the centrifugal section of the pan stage. Within the KBSSS this model is directly used to provide information in the determination of:

- C sugar footings to A/B seed pans which is a core system recommendation for the production of quality sugar of specification size sugar;
- Long term expected final molasses and product sugar rates and purity; and
- Average remelt rate for use in prediction of liquor stock tank levels.

The major equipment item sets, as depicted in Figure 13, utilized in this model are:

Pans {A Seed, B Seed, C Seed, A, B, C}

Fugals {A, B, C}

Massecuite Receivers {A, B, C}

Tanks {Remelt, Liquor, Final Molasses, A molasses, B molasses, C molasses}

Sugar Screws {A, B, C}

Bins {Product Sugar}

Each equipment item is modelled in software using the object oriented approach. Typically each item has data members for output solids flow rate and purity. The liquor, A molasses and B molasses tanks, B sugar screw and C sugar screw additionally have their output product being fractionally split and consequently have these flows used as feed material for other equipment items on the pan stage. This solids flow information is stored against the producing item along with the fractional values used in splitting these flows. The occurrence of fractional splits to other devices is visually represented in Figure 13. The model is capable of varying pan stage arrangements under the three massecuite boiling scheme through customization of the product fractions from the major equipment devices. The default model parameters used (Dodd, Broadfoot, Chiou and Yu, 2008a) are typical of mid seasonal sugar factory conditions for the production of Brand 1 grade sugar (Broadfoot and Pennisi, 2001).

In following the three massecuite boiling scheme, which is common for pan stage sugar processing within Australian sugar mills, there exists three major process streams within the model. These are the production of A sugar, B sugar and C sugar. C sugar is used as footings for the production of A and B sugar with the excess sent to the remelt tank. A and B sugar are combined to form the final product sugar. The A molasses and B molasses products result from fugalled A and B massecuite respectively and along with liquor are used as feed products in the A, B and C sugar production segments of the process. C

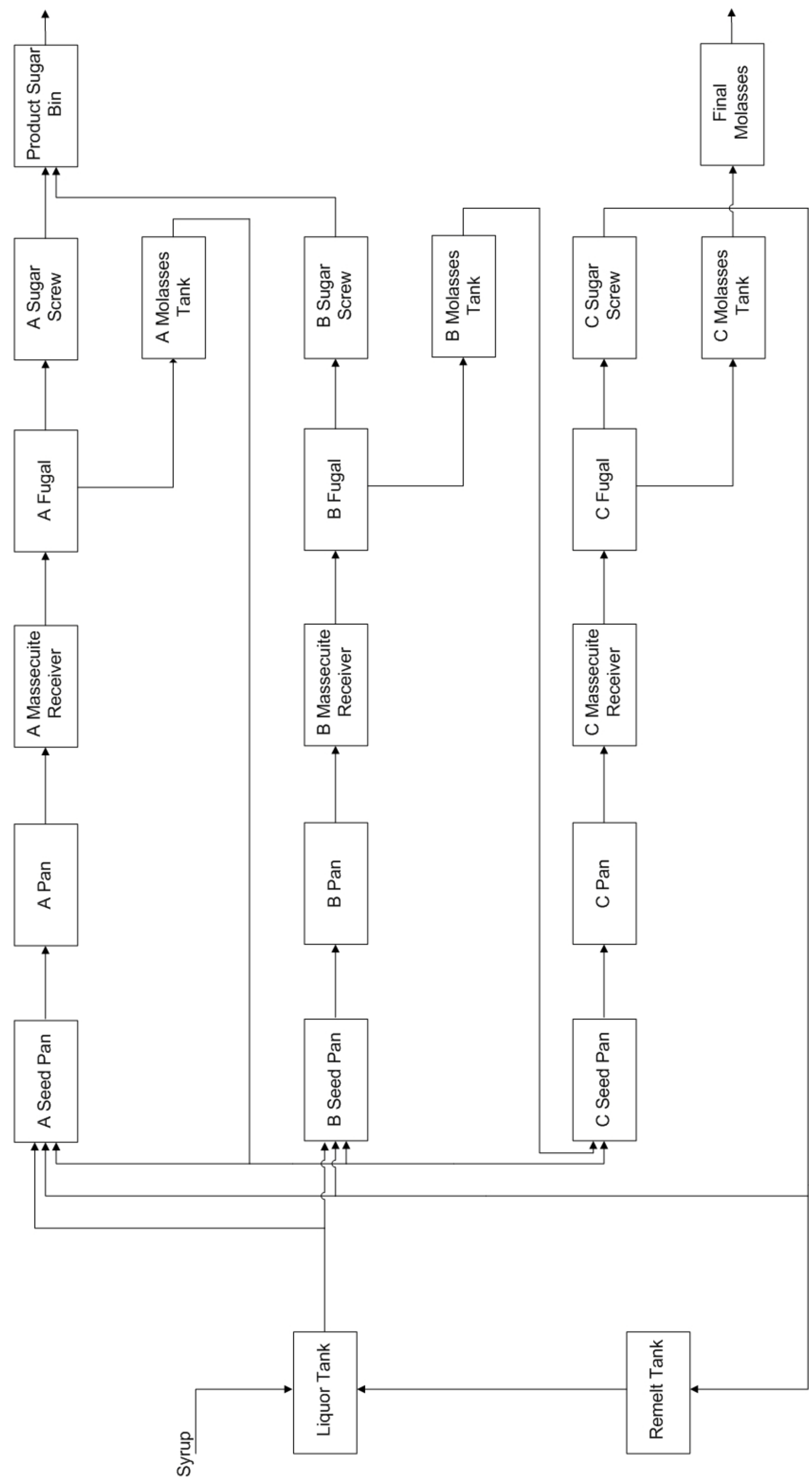

Figure 13: Pan stage steady state flow model

molasses from fugalled C massecuite is sent for storage as final molasses, and sold.

The overall algorithm, as presented in Figure 14 consists of two main program loops with several conditional branches ensuring purities of the seed pans are achieved through local optimization. Calculations to ensure C sugar footings to the seed pans produce product sugar within the nominated specification size are also performed. All initial flows are set to small positive values to allow calculation of process material flow purities during the first iteration through the flow update loop.

The key model input is the syrup rate and purity to the liquor tank which is the first major item in the overall model. Customizable model parameters are used to establish initial conditions for the model. The setting of key model parameters guides the initial flows and purities on the seed pans and flows are sequentially fed forward throughout the network.

The primary loop controls purity and sugar sizing calculations and contains a secondary loop responsible for calculations of equipment item flows and purities and validation using mass balance checks. After the primary loop runs the secondary loop it checks to see if the maximum number of iterations for the mass balances has been reached or if all the mass balances have converged to within specified limits. If neither of these conditions has been reached the inner secondary loop is repeated until one is met. Otherwise control moves back to the primary loop.

Within the secondary loop, flow and mixed purity calculations (Sugar Research Institute, 2000) are used to determine process material solids flow rates and associated purities for each equipment item in the model. A mass balance (Bureau of Sugar Experiment Stations, 1984) on each equipment device is then conducted to ensure that the quantities of sugar solids entering a device is equivalent to that leaving adhering to a set tolerance value for calculations. Process material flows essentially feed forward through the network, during each secondary loop iteration, one device at a time and radiating outwards from the primary syrup input to the liquor tank.

After completion of the secondary loop control passes back to the primary loop. A check is made to see if the A massecuite purity of the A seed pan is within allowable target limits. If this has not occurred fractional changes to the split of A molasses quantities from the A

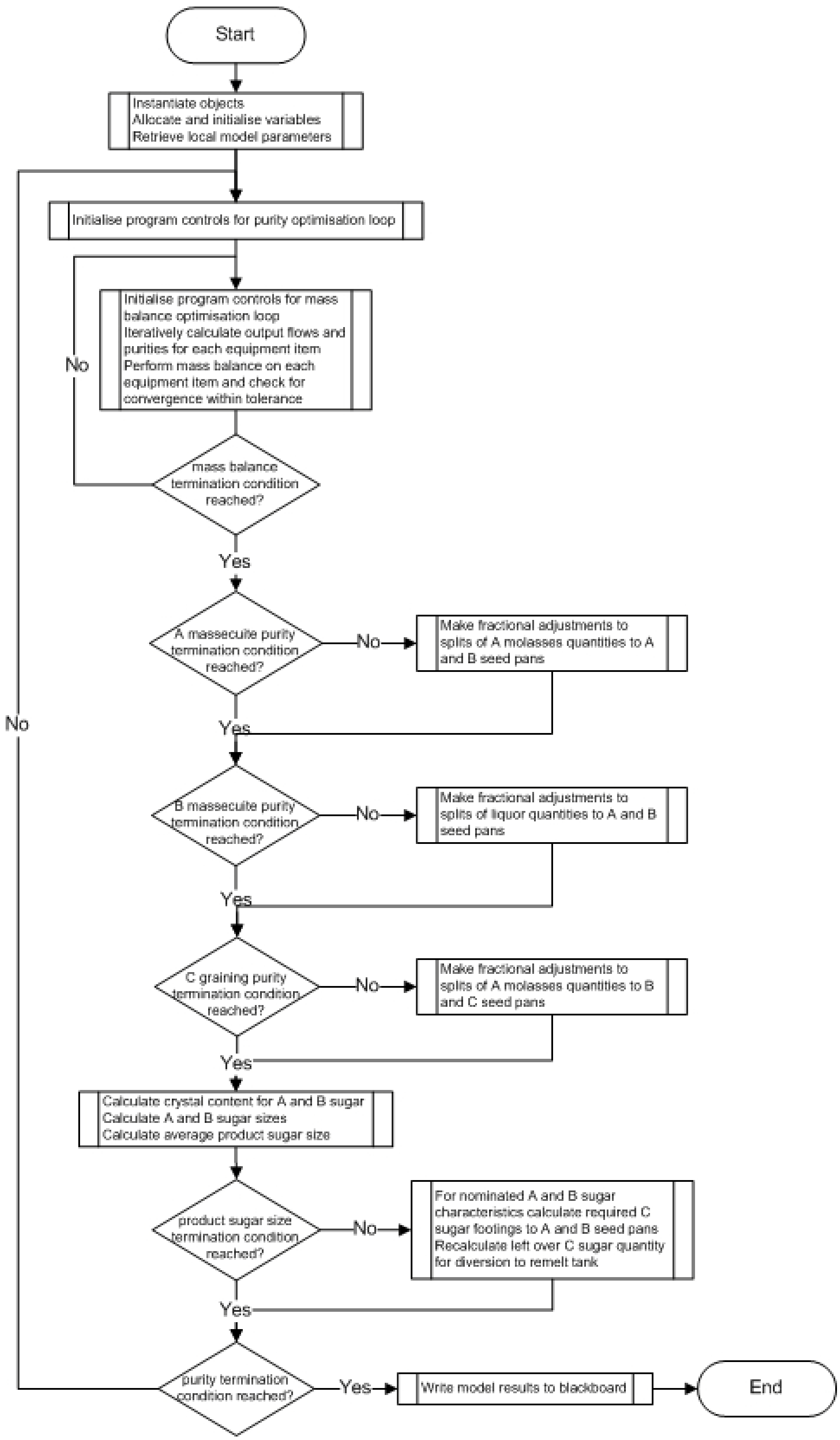

Figure 14: Pan stage steady state flow model algorithm

molasses tank to the A and B seed pans are made to incrementally adjust the A massecuite purity towards the target.

Next a check is made to see if the B massecuite purity of the B pan is within allowable target limits. If this has not occurred fractional changes to the split of liquor quantities from the liquor tank to the A and B seed pans are made to incrementally adjust the B massecuite purity towards the target.

One final purity check is made. This is to determine if the C graining purity of the C seed pan is within the allowable target limits. If this has not occurred fractional changes to the split of A molasses quantities from the A molasses tank to the B and C seed pans are made to incrementally adjust the C graining purity towards the target.

After this series of purity checks and calculations are carried out, a check on the sugar sizes is performed through calculation of the A and B sugar sizes as well as the combined product sugar. If the product is not within the allowed limits, for the nominated A and B sugar characteristics, calculation of the required C sugar footings to the A and B seed pans is performed. Since these sugar quantities come from the C fugals the excess quantity of sugar that is not used for footings is calculated for diversion to the remelt tank. The crystal sizing calculations (Broadfoot, 2004a) determine the necessary quantities of C sugar needed for the A and B seed pans to ensure final product sugar is within specified size and tolerance.

This sequence of operations with the initial secondary loop operations is iteratively performed as part of the primary loop. This continues until the maximum number of purity iterations has been reached for the optimisation process or all target purities have converged.

The final model results are solids flow rates and purities for each equipment device, and sugar sizing information along with convergence data for target purities and mass balances for each equipment item. The solids flow excludes the quantity of water present in practice. A conversion to actual flows is made at the successful completion of the model. The model results are then written to a blackboard system resulting in algorithm completion.

5.2.3 Empirical Vacuum Pan Models

Individual pan production rates have been modelled by constructing empirical relationships (Dodd, Broadfoot, Yu and Chiou, 2005b) for the rate at which each pan uses feed material (liquor, A molasses or B molasses) during each phase of the pan's strike. This boil-on rate for feed materials is a function of the massecuite level and phase of the pan, steam rate, head space pressure (vacuum), brix and purity of the feed liquor/molasses. Using this method it is possible to construct a piece-wise model of pan feed rate characteristics during each phase of the pan's operation for each of the vacuum pans. Figure 15 illustrates the empirical model phases for Racecourse mill batch vacuum pan number 3 level with respect to time during A massecuite strikes on 04/09/2003. Feed material consumption rates are associated with each of these phases to build a piece-wise model for operation over the entire strike.

The batch vacuum pan empirical pan models have the following set formulations:

batch vacuum pans = $\{b_1, b_2 \ldots b_i\}$

where,

***i** is the number of batch pans operating within the pan stage schedule.*

$duty_j = \{d_1 \ldots d_j\}$

where,

***$duty_j$** is the defined massecuite production duty for batch vacuum pan i. It is important to note that only batch vacuum pans designated as "swing" pans will have both A and B massecuite production duties.*

$phases_{ij} = \{p_1, p_2 \ldots p_k\}$

where,

***k** is the number of phases for batch pan i associated with massecuite production duty j.*

$data_{ijk}$ = {syrup feed rate, A molasses feed rate, B molasses feed rate, phase duration, time since start of pan strike to commencement of phase}

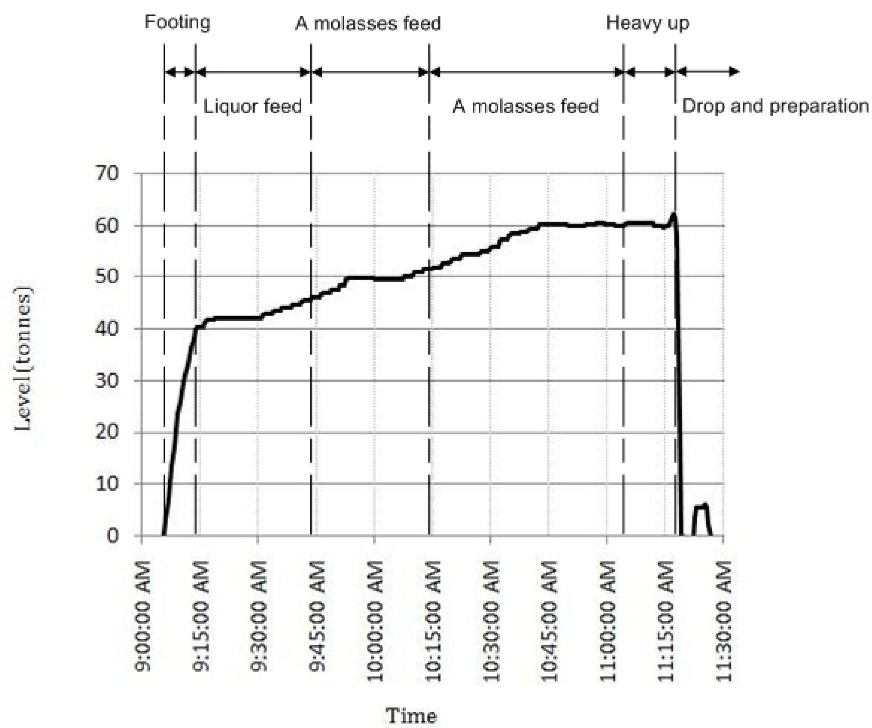

Figure 15: Racecourse mill batch vacuum pan number 3 level vs time during A massecuite strikes on 04/09/2003 annotated with empirical pan model phases.

where,

data$_{ik}$ *is phase information for the kth phase of batch vacuum pan i with duty j.*

This series of models is maintained and stored as series of database records for each of the vacuum pans assigned duties. For each phase, information on its duration and syrup, A molasses and B molasses feed rates is stored along with required time from the start of the pan strike to when the actual phase commences.

Time since pan strike has commenced (min)	Phase duration (min)	A molasses feed rate (t/h)	B molasses feed rate (t/h)	Syrup feed rate (t/h)	Phase information tag
0	8	0.00	0.00	0.00	Footing
8	31	0.00	0.00	15.24	Liquor feed
39	33	18.54	0.00	0.00	A molasses feed
72	52	16.65	0.00	0.00	A molasses feed
124	16	0.00	0.00	0.00	Heavy up
140	103	0.00	0.00	0.00	Pan drop and preparation for next strike

Table 1: Empirical pan model phases and feed rates for Racecourse mill batch vacuum pan number 3

An example of the empirical pan model phases and their associated feed rates for the batch vacuum pan in Figure 15 is presented in Table 1. The feed rate information and phases are derived from the empirical pan model information in Appendix B. A piecewise model is similarly constructed for each batch vacuum pan in the pan stage schedule and stored within the KBSSS local parameter database for the empirical pan models.

Due to the uniform nature of continuous vacuum pan operation, feed material consumption rates and consequently information storage differ compared to batch vacuum pan empirical models. Empirical vacuum pan models for continuous batch pans require substantially less information and are simpler than batch vacuum pans and can be modelled using a much more compact data representation. This is due to not having to store information on strike phases or information on differing massecuite production duties. Continuous vacuum pans have a single defined massecuite production duty and essentially continuous process material feed rate requirements.

Continuous vacuum pan empirical pan models have the following set formulations:

continuous vacuum pans = $\{c_1, c_2 \ldots c_k\}$

where,

k *is the number of continuous vacuum pans operating within the pan stage schedule.*

continuous_data$_k$ = {syrup feed rate, A molasses feed rate, B molasses feed}

where,

continous_data$_k$ *is the set of material feed rates for operation of continuous vacuum pan k.*

A molasses feed rate (t/h)	B molasses feed rate (t/h)	Syrup feed rate (t/h)
0.00	27.00	0.00

Table 2: Empirical pan model feed rates for Racecourse mill continuous vacuum pan number 8

An example of feed rates for the continuous vacuum pan number 8 at Racecourse sugar mill is presented in Table 2. The feed rates for this continuous vacuum pan model is determined empirically and presented in Appendix B. Racecourse sugar mill only has a single continuous vacuum pan for massecuite production on the pan stage, however this information format for empirical modelling of continuous vacuum pans would be also used if there was other continuous vacuum pans operating within the schedule.

This compact data set representation models the process material feed rates for continuous vacuum pans. This information, similar to the batch vacuum pan representation is also stored as a series of database records. These empirical vacuum pan models are maintained as a database lookup system and used in combination with the vacuum pan phase determination models, proposed in the next section. The vacuum pan phase determination models generate the sequence of phases that a pan will go through over a specified forecast period. This is then extended through incorporation of the feed rates, from the empirical vacuum pan models, within the sequence of phases to assist in determining feed quantities used from stock tanks for vacuum pan operations. This information is a major feature of the stock tank models presented in Section 5.2.5.

5.2.4 Vacuum Pan Phase Determination and Forecast Model

This model determines the phase of the strike each batch vacuum pan is currently operating in and then dynamically builds a sequence of phases over the defined prediction period using phase information from the empirical pan models. This model takes advantage of the repetitive pan stage schedule and consistency in successive pan strikes due to the pan stage operating schedule. Figure 16 shows Racecourse sugar mill batch vacuum pan number 3 performing A massecuite duties on 04/09/2003 and presents level details for three successive strikes over a twelve hour period. The repetitive nature of batch vacuum pan operations, under standard operating conditions, is highlighted by this diagram and this repetitive nature is similarly evident for the other batch vacuum pans on the pan stage.

The software algorithm for this model is presented in Figure 17. This model makes use of the empirical batch vacuum pan models, as presented in Section 5.2.3, as primary input to build a similarly repetitive schedule of future pan phases over the forecast period. This sequential phase allocation is similar to that in Figure 15 however over a much greater time period. The extended time period required is determined by the forecast period.

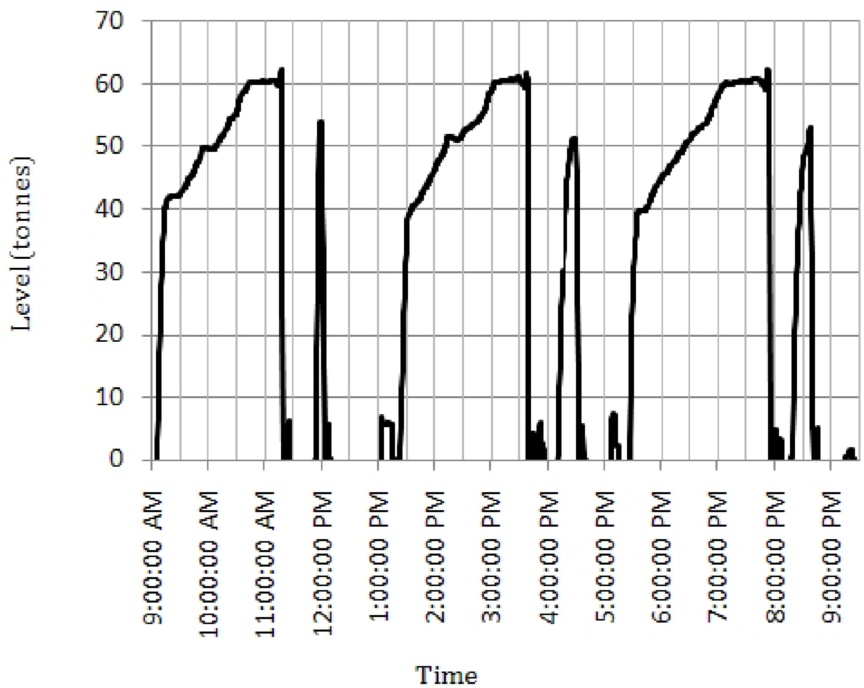

Figure 16: Racecourse mill batch vacuum pan number 3 level versus time during A massecuite strikes on 04/09/2003

For each batch vacuum pan, current massecuite production duties are determined and the appropriate empirical pan model lookup for the vacuum pan is performed. A determination is then made using the time of the last pan strike commencement which is used as the reference point for the forecast. Calculations using phase information, from the empirical vacuum pan models, are used to determine at what point of which phase the pan is currently operating in and how much time in this phase has elapsed. With the current operating phase determined, a repeatable sequence of phases that the pan will proceed through during each strike is dynamically generated over the specified forecast period.

Two main event loops comprise the fundamental structure of the algorithm. The outer loop passes information on each batch vacuum pan in the schedule to the inner loop. The inner loop performs a lookup of empirical pan model data for each batch vacuum pan under scheduled production duties. This information is then transformed into a data set consisting of the starting time of phase, A molasses feed rate, B molasses feed rate and syrup feed rate. The If-Then-Else statement block that forms the majority of processing within the inner event loop determines the starting time of the phase.

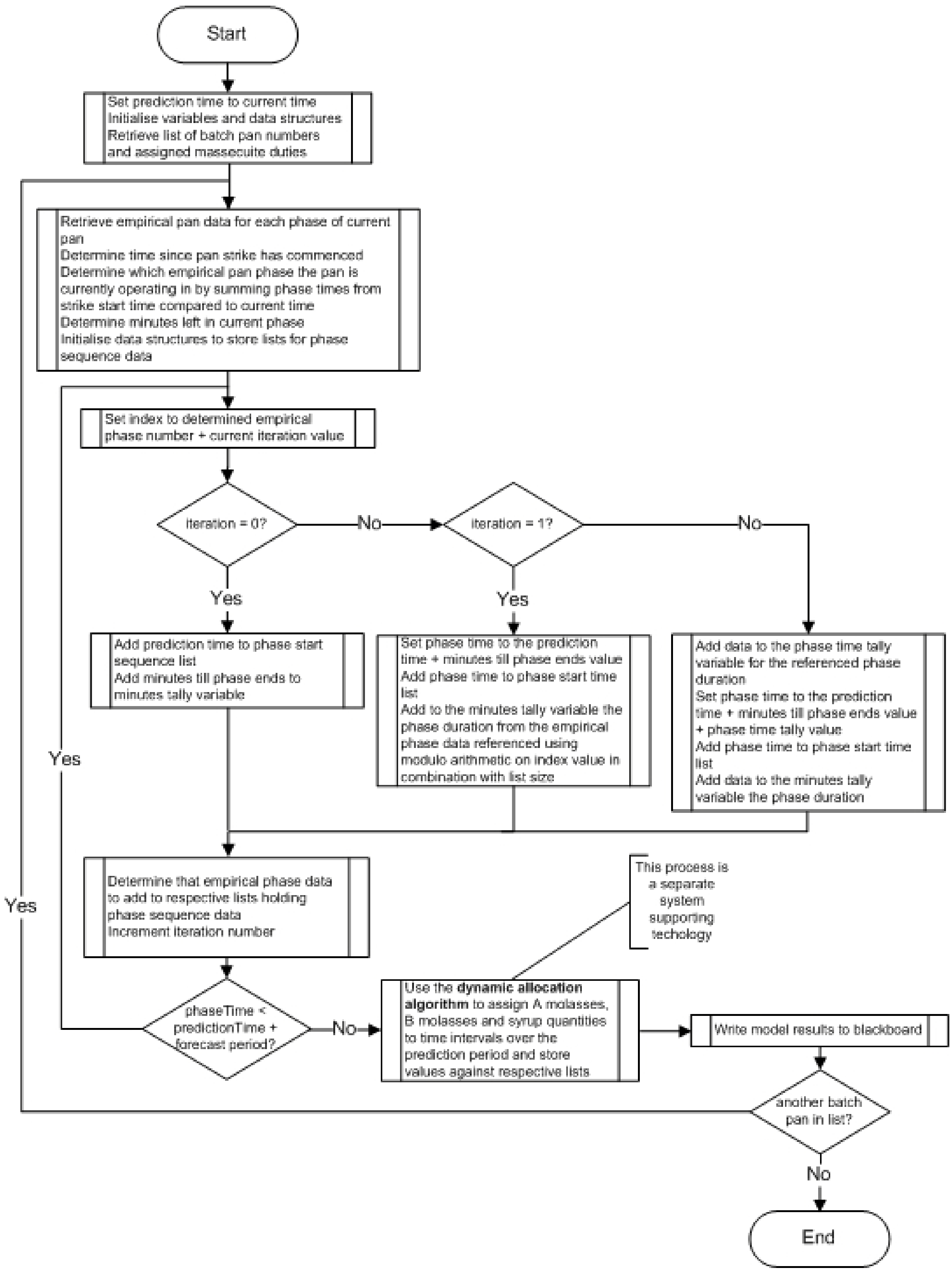

Figure 17: Vacuum pan phase determination algorithm

A sequence of these data sets, representing the scheduled sequence of phases, is determined over the specified forecast period. This represents the sequence of scheduled phases that the vacuum pan will go through as part of the pan strike operations. These processed data sets are now in the correct format to be parsed by the dynamic allocation algorithm, detailed in Section 5.3.1. This algorithm determines forecast intervals over the prediction horizon, discretized into predefined periods, and apportions feed material quantities to each period. Results of the model are then passed to the blackboard system for information storage and access by further pan stage process models and KBSSS subsystems.

By coupling the previously described empirical pan models, from Section 5.2.3, the feed materials quantities used over the forecast period can be determined. This information is a key requirement in the stock tank predictive models presented in Section 5.2.5.

5.2.5 Stock Tank Predictive Models

Considering the problem of stock tank interaction on the pan stage, a mass balance (Bureau of Sugar Experiment Stations, 1984) over a generic stock tank yields the governing differential equation as:

$$\frac{dLevel}{dt} = Supply - Demand \tag{5.3}$$

where,

Level *is the stock tank level,*

Supply *is the process return streams to the stock tank,*

Demand *is the process feed streams from the stock tank.*

Equation (5.3) leads to the following liquor tank model:

$$L_{(t+1)} = L_{(t)} + \int_t^{t+1} S\,dt + \int_t^{t+1} R\,dt - \int_t^{t+1} F\,dt \tag{5.4}$$

where,

L *is the liquor tank level,*

S *is the syrup process stream input,*

R *is the remelt sugar process stream return,*

F *is the syrup feed rates for all vacuum pans,*

t *is a specific point in the overall pan stage schedule.*

Equation (5.3) also leads to the following generic molasses tank model, with application to both A molasses and B molasses stock tanks:

$$M_{(t+1)} = M_{(t)} + \int_t^{t+1} C\,dt - \int_t^{t+1} V\,dt \tag{5.5}$$

where,

M *is the molasses tank level,*

C *is the centrifugal molasses process stream return,*

V *is the molasses feed rates for all vacuum pans,*

t *is a specific point in the overall pan stage schedule.*

Vacuum pans, producing massecuite to be used for processing to product sugar, have their contents dropped to receivers. These receivers are used as temporary storage before the centrifuging process and allow the vacuum pans to continue in their next strike. As detailed in Section 2.3 the massecuite is processed by the centrifugals on the fugal station resulting

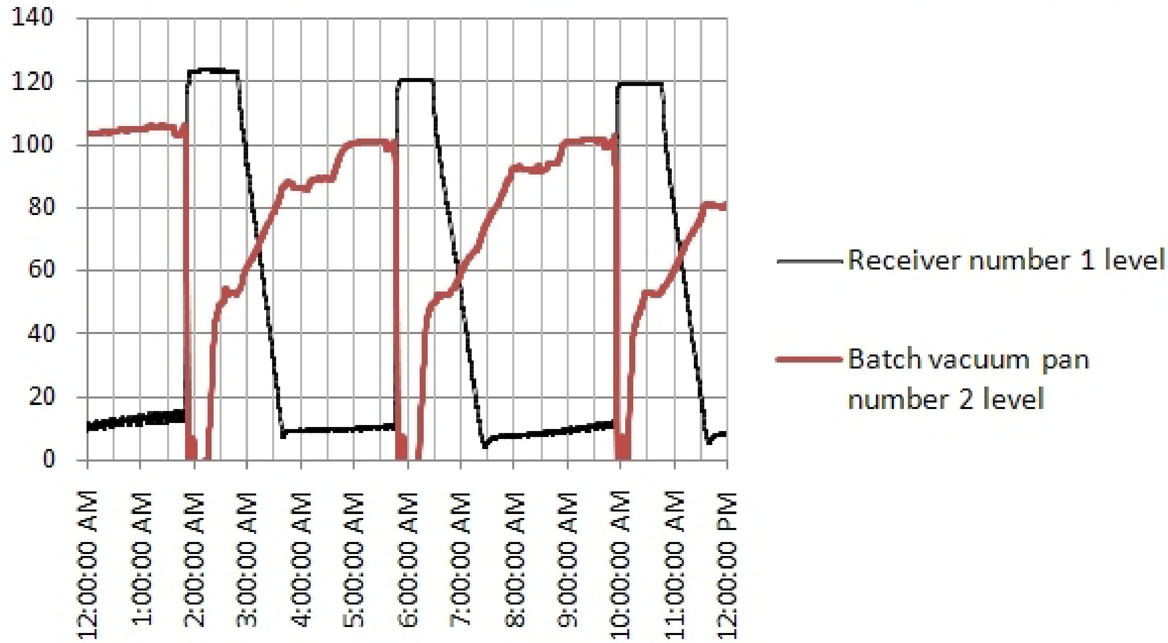

Figure 18: Fugalling model characteristics for the fugalling of Racecourse mill receiver number 2

in the intermediate products of molasses and raw sugar. This processing regime is repetitive due to the nature of the pan stage schedule and highlighted in Figure 18.

This process is modelled through the following method. Upon pan drop the massecuite contents of the pan are transferred to the receiver. After a fugalling delay the contents of the receiver are fugalled at a steady rate until the receiver reaches a minimum level. These three key pieces of information comprise the fugalling model of the receivers - fugalling delay, fugalling rate and minimum receiver level. This relationship is presented in Figure 19.

The pan to receiver relationship and fugalling models have the following set formulations:

batch vacuum pans = $\{b_1, b_2 \ldots b_i\}$

where,

i *is the number of batch pans operating within the pan stage schedule.*

receivers = $\{r_1, r_2 \ldots r_j\}$

where,

j *is the number of receivers operating within the pan stage schedule.*

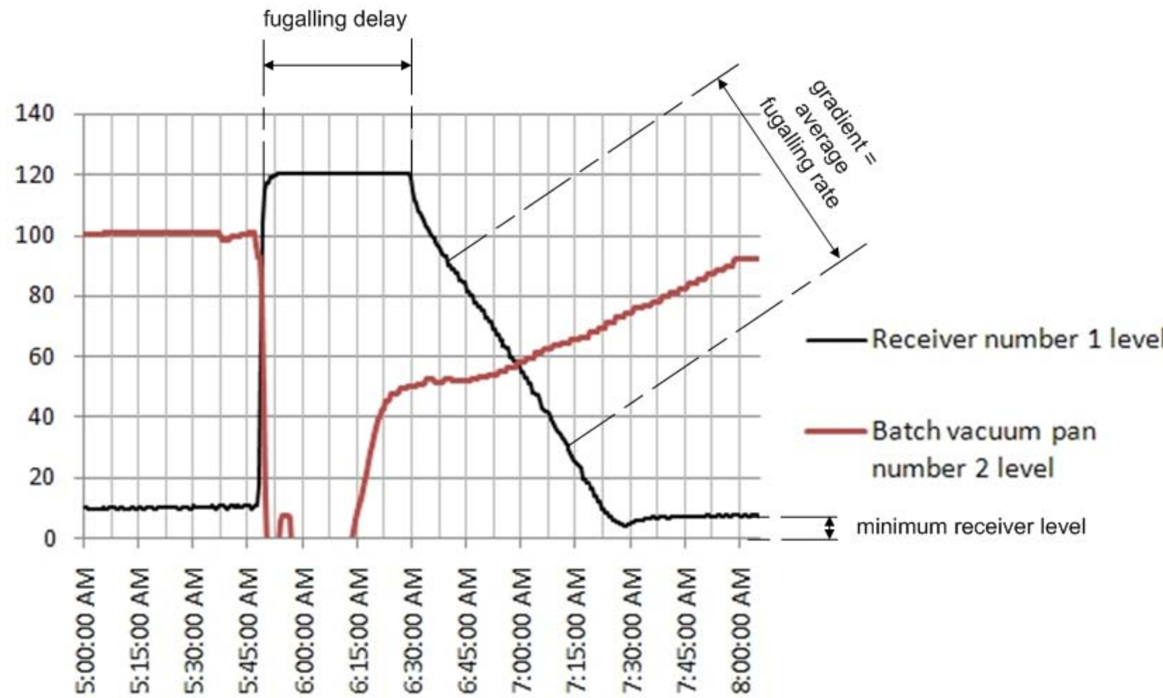

Figure 19: Racecourse mill batch vacuum pan number 2 dropping to receiver number 1 during strikes on 02/09/2003

receiver $data_j$ = {receiver number, minimum receiver level, fugalling rate}

where,

***receiver** $\boldsymbol{data_j}$ is the receiver information stored for the kth receiver.*

pan-receiver $data_{ij}$ = {batch vacuum pan number, receiver number, average fugalling delay}

where,

***pan-receiver** $\boldsymbol{data_{ij}}$ is information relating the ith batch vacuum pan dropping to the kth receiver.*

Batch Vacuum Pan Number	Receiver Number	Average Fugalling Delay (min)
2	1	42

Table 3: Pan to receiver relationship data for pan number 2 dropping to receiver 1

Receiver Number	Minimum Receiver Level (t)	Average Fugalling Rate (t/h)
1	10	120.80

Table 4: Fugalling model data for receiver number 1

An example of batch vacuum pan to receiver relationship and fugalling model is presented in Table 3 and Table 4 respectively for batch vacuum pan number 2 dropping to receiver number 1. This relationship corresponds to Figure 19 displaying receiver and pan levels for fugalling performed on 03/09/2003. The average fugalling delay, minimum receiver level and average fugalling rate are determined empirically from this historic pan stage control system data.

The complicating factor due to the pan stage schedule arrangement is to handle the condition when multiple pans are dropped to the one receiver. This may necessitate the fugalling of several quantities of massecuite, depending upon scheduled drop times, with these dropped quantities occurring at close intervals. Massecuite drops to receivers occur from different pans scheduled to perform the same product massecuite duties. This

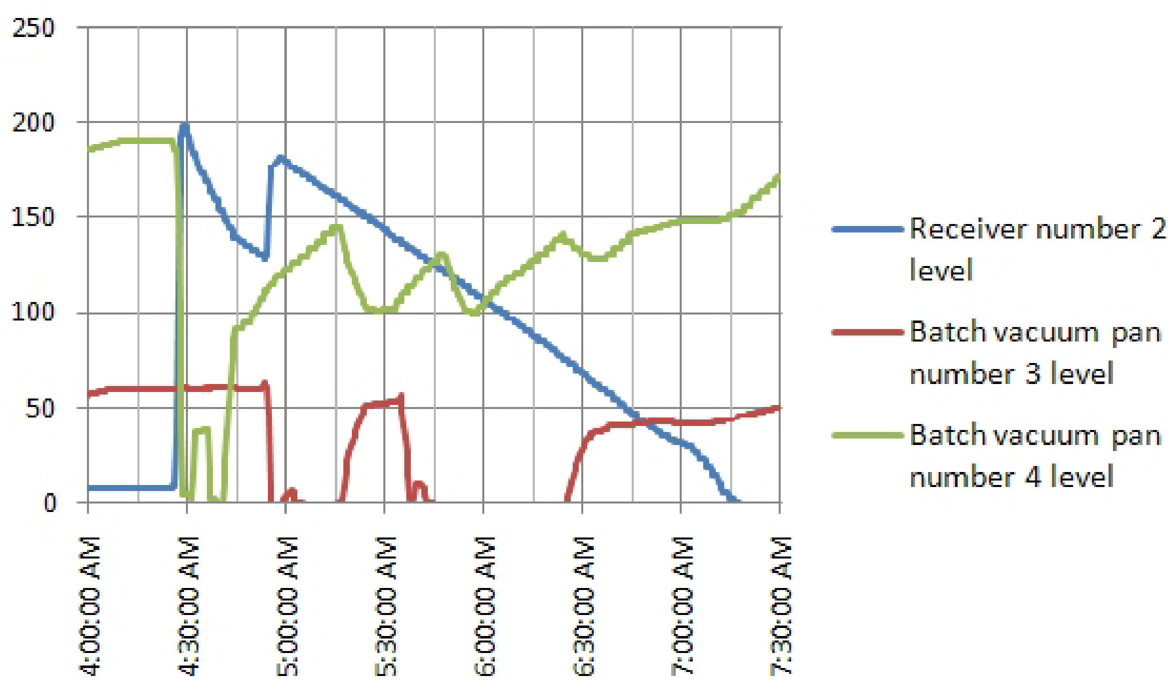

Figure 20: Batch vacuum pans numbers 3 and 4 dropping to receiver number 2 after completion of strikes on 03/09/3003

situation is highlighted in Figure 20 where batch vacuum pans 3 and 4 drop massecuite to receiver number 2 during strikes performed on 03/09/2003. Pan number 4 drops massecuite product to receiver number 2 at approximately 4:30am. The fugals then commence operation and the receiver levels drop due to the fugalling process. At approximately 4:50am pan number 3 drops its product massecuite and the receiver level rises. This final massecuite quantity is then fugalled until the receiver is emptied.

The software algorithm provides a syrup tank level prediction through the collation of data governed by the stock tank level equation in Equation (5.4). Some further information processing is required in quantifying the molasses return quantities from the centrifugal station for determination of molasses tank levels governed by Equation (5.5). The stock tank level model is dependent upon the models presented in Section 5.2.1 through to Section 5.2.4. The syrup prediction model, pan stage steady state flow model, phase detection and forecast model, working in tandem with the empirical pan models, all contribute information towards stock tank level model.

The overall algorithm consists of three main event loops with associated information processing and presented in Figure 21. The algorithm starts after the phase determination and forecast algorithm has been run to determine syrup and molasses feed quantities for the batch and continuous pans over the forecast horizon. The syrup feed quantity information from this model is collated with the current syrup stock tank levels, average C sugar remelt rate from the steady state pan stage flow model and syrup production quantities from the syrup rate production model to build a forecast of stock tank levels. After collation this information is then stored to the system blackboard. Fugalling information is retrieved from the pan stage steady state flow model for later use along with the list of receivers.

The main event loop processes information iteratively for each receiver. For each receiver the pans dropping to it along with their assigned massecuite duties are determined. Dependant upon massecuite production duties additional fugalling information is retrieved from the blackboard for the pan stage steady state flow model results. Within the event loop a further two loops perform the bulk of processing work.

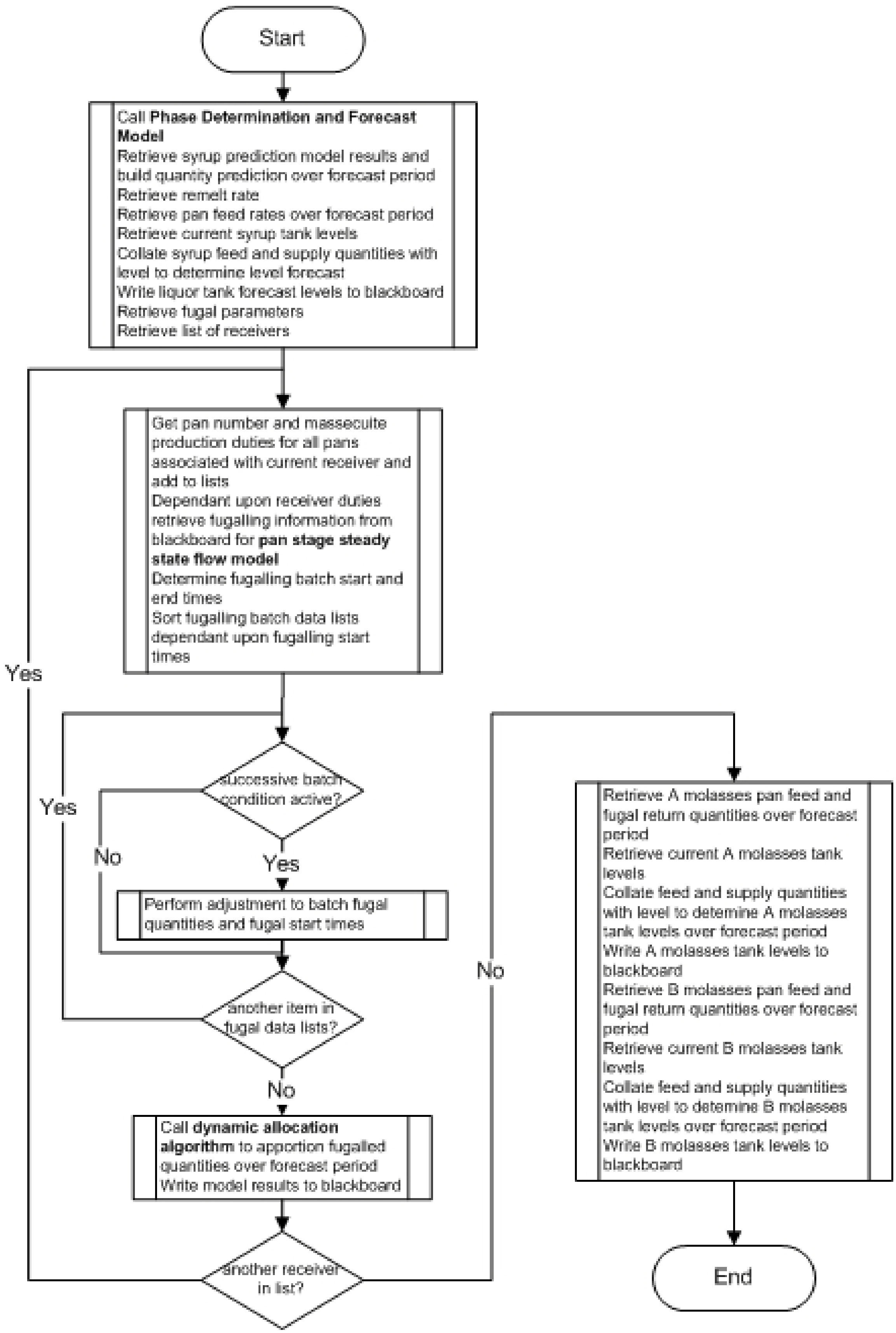

Figure 21: Stock tank model algorithm

The first loop continues the described processes and iteratively builds a projected list of pan drops over the forecast horizon. For each pan dropping to the current receiver, within this event loop, the algorithm the last known pan drop quantity and time of drop along with duration of the pan strike. For the pan drop the associated fugalling start time, duration and end time is calculated and added to data lists tracking this information. Over the forecast period a sequence of this information is constructed for each projected pan drop for each of the pans dropping to the receiver. Since multiple pans may have dropped to a receiver this series is lists is sorted depending upon the fugalling batch start times.

The second loop performs an update on batch quantities to be fugalled if a successive batch occurs within the expected fugalling duration of the current batch. Each batch is iteratively processed and this check performed. If this occurs the quantities associated with the current and successive batch are adjusted. The current batch to be fugalled will not be processed for the previously expected duration. Instead processing only runs until the successive batch is scheduled to run. The remaining quantity of massecuite to be fugalled is added to this successive batch.

Once all the batches to be processed from the receiver have been checked then batch information is passed to the dynamic allocation algorithm. This algorithm, as detailed in Section 5.3.1, is used to apportion the molasses quantities from the fugalling process to discrete intervals over the forecast prediction period and writes the results to the system blackboard. This concludes the processing regime for the main event loop.

In a similar fashion to the collation of data for the syrup stock tank levels, a similar process is performed to predict stock tank levels for both A and B molasses. The molasses return rates from the described algorithm are collated with the current molasses stock tank levels along with molasses feed rates projected from the phase determination and forecast model. Final tank level results for both A and B molasses tank level predictions over the forecast period are then stored by the system blackboard. The algorithm then terminates.

5.2.6 Schedule Optimisation

Using the previously established pan stage steady state flow model in conjunction with multi parameter optimization, the scheduling of when pans should start and complete strikes can be made in order to avoid vacuum pan idling time, while minimizing steam usage on the overall pan stage and adhering to sugar production productivity, recovery and quality requirements. This is accomplished through the adjustment of the length of the legs in the pan stage schedule. The high grade pan stage schedule for Racecourse sugar mill 2003 cane crushing season is presented in Figure 22. The elementary cycle time for each leg of pan strikes is to be noted.

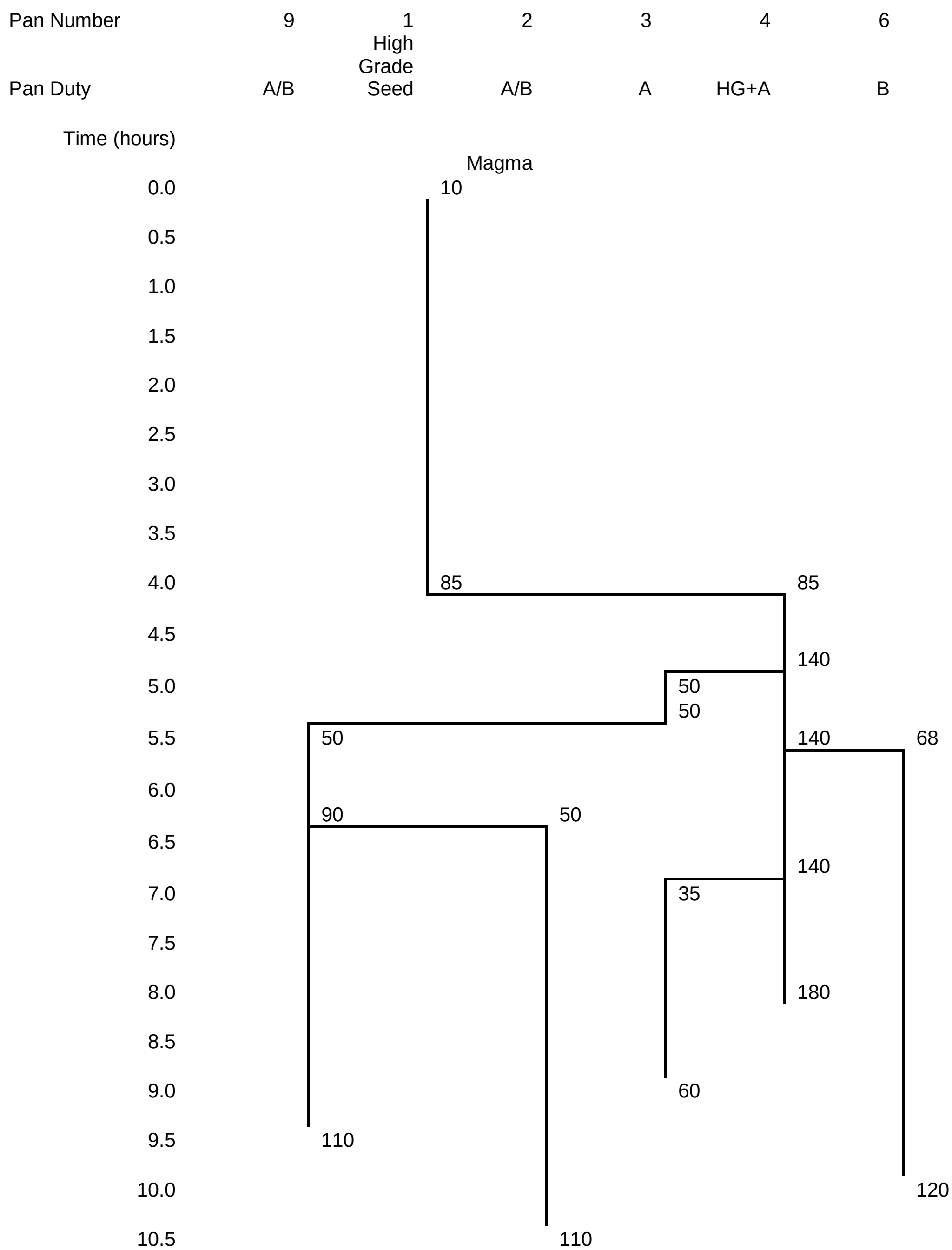

Figure 22: Racecourse mill pan stage high grade schedule used during 2003 cane crushing season

Previous research (Sugar Research Institute, 2000) indicates the importance of the following rules for scheduling:

- The leg for each pan in the schedule must be of the same duration. The longest duration for any leg in the schedule is known as the elementary cycle time and is the time taken for a particular point in the pan strike cycle to reappear. Any pan running on a cycle time shorter than this will gain no benefit and will instead have to wait for pan stage operations to catch up. This imposes a limit to cycle time being the duration of the slowest leg of operation.

- Idling time for pans should be minimised or totally prevented. Instead each pan should run for the duration of the schedule cycle time.

- Strike pans should be staggered to enable better use of receivers and fugals for massecuite processing. This also assists in staggering the demands for molasses and syrup process materials throughout pan strikes.

- Some flexibility should be allowed to accommodate the boiling of extra A/B massecuite for swing pans. The A/B ratio is typically in a range of 1.5 to 2.5 and the schedule arrangement may not exactly match for the pan stage sugar boiling formula. Occasionally an extra A or B pan will be required to bring molasses stock tank level into balance.

The key criteria for optimal scheduling are the sugar quality, pan stage recovery, vacuum pan steam rate usage and pan stage productivity. These concepts interrelate and often co-compete. These criteria are now discussed in terms of building an optimal schedule for pan stage operations:

Sugar quality. The ten quality parameters introduced for the 2003 raw sugar quality scheme (Queensland Sugar Corporation, 2003) were defined as polarisation, moisture, ash, filterability, starch, fine grain, colour, dextran, specific soluble impurities and temperature with bonuses of $1.50 to $5.00 per tonne as part of a sliding scale bonus achieved in sugar production for sugar meeting all ten of the criteria. As part of these bonuses it is considered (Broadfoot, 2004b) that pan stage operations could influence bonuses of $2.50 to $3.00 per tonne of sugar produced. The pan stage can only assist in meeting some of these criteria.

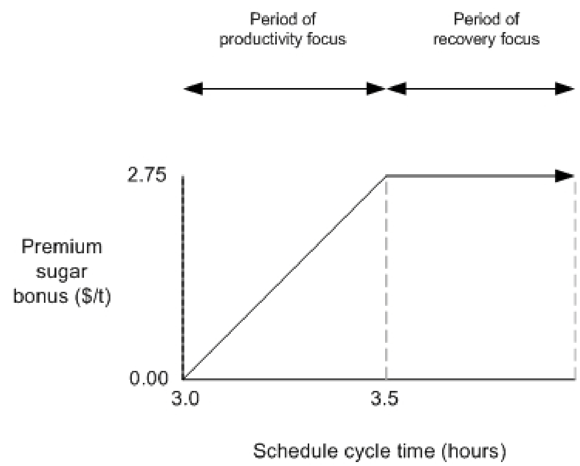

Figure 23: Premium sugar bonus related to schedule elementary cycle time

The time taken for pan duties essentially defines the sugar quality criteria of "fine grain". This in turn is indirectly responsible for other factors of pol consistency at the fugals and temperature and moisture at the dryers. In relating sugar production premiums back to the pan stage schedule it is envisaged that if pan cycle times are greater than 3.5 hours in length there is certainty that quality premiums of $2.50 to $3.00 per tonne of sugar will be achieved. For pan cycle times of less than 3 hours the likelihood of obtaining premium sugar is assumed to be zero. A linear relationship is assumed to exist between these two points with a graph of this relationship presented in Figure 23. The bonuses likely to be achieved by the pan stage are taken as the mid range value of $2.75 per tonne.

Pan stage recovery. The pan stage steady state model already provides quantification of the long terms flows and purities for pan stage process materials. Modified input parameters for the final crystal content of vacuum pans dropping as a function of pan cycle time are used as a primary input for the pan stage steady state flow model. Shorter pan cycle times yield less exhaustion (ie lower cystal content factors) with the affect of higher A and B molasses purities and consequently higher C massecuite purity. Essentially a C massecuite purity rise of 1 unit will increase C molasses purity by 0.4 units. Previous research (Broadfoot, 2002) shows that a final molasses purity drop from 46.5% to 45.5% for a factory processing 2 million tonnes of cane in a season could increase revenue by $191, 640. This quantifies the financial value of the amount of sucrose tied up in the final molasses stream.

Vacuum pan steam rate usage. Steam usage rates affect the pan duty time and hence pan productivity rate. The aim is to minimise steam on the non-critical legs of the schedule. However no overall benefit is produced if legs in the schedule for any individual pans exceed their defined cycle time. A pan exceeding the elementary cycle time of the pan stage schedule must wait (ie. *idle)* until the other operations catch up. The aim is to make use of the full length of the allocated cycle time and avoid idling of pans.

For simplification of modelling and inline with the steam rate modelling approach presented in Appendix B a fixed steam rate is assumed over the pan cycle times to approximate actual rates. It is noted that steam ramping occurs after the initial pan footing phase is undertaken with total steam cut off during periods of pan content transfers and a decline before pan drop. However these periods form a minor part of the overall strike duration.

Pan stage productivity. Increasing vacuum pan steam rate, particularly on pans in the critical legs of the schedule, will increase throughput and likely result in lower steam usage per tonne of sugar produced. However with constrained supplies of sucrose available, through syrup quantities forming the pan stage input, the pan stage cannot be driven any harder than to accommodate processing of the current syrup supply – even if it is capable. Driving pans harder through increased steam usage will result in reduced crystal content of the final massecuite. This competes against the objective of increased recovery of the pan stage. For the production rates and operating conditions forecast the best choice of A/B massecuite production duties must also be determined.

When the cane CCS is low, which is typical of early and late season conditions (Broadfoot and Pennisi, 2001) with peak CCS occurring during mid-season, the A and B massecuite production rates will be lower with longer cycle times available for the pan stage schedule. The aim should be to use the time for returns from increased recovery, improved quality and reduced steam usage. Figure 23 indicates the period of focus for this improved recovery with longer cycle times to be scheduled dependant upon the point of season.

The overall objective is to maximise profit from the sugar creation process with molasses by-product accounting for the costs of steam and the bonuses for quality sugar production. The profit function is defined as:

$$P = \int_{t_0}^{t_1} M_V * M_R \, dt + \int_{t_0}^{t_1} (S_V + B) * S_R \, dt - \sum_{n}^{i=1} \int_{t_0}^{t_1} C_V * C_n \, dt \tag{5.6}$$

where,

***P** is the profit value in dollars,*

$\boldsymbol{M_V}$ is the value of product molasses in dollars,

$\boldsymbol{M_R}$ is the molasses production rate in tonnes per hour,

$\boldsymbol{S_V}$ is the value of product sugar in dollars,

***B** is the premium sugar bonus in dollars,*

$\boldsymbol{S_R}$ is the sugar production rate in tonnes per hour,

$\boldsymbol{C_V}$ is the value of steam in dollars,

$\boldsymbol{C_n}$ is the steam rate in tonnes per hour for vacuum pan n,

$\boldsymbol{t_0}$ is the initial point in time,

$\boldsymbol{t_1}$ is the point in time from $\boldsymbol{t_0}$ with separation of the strike cycle duration.

The equation presented in Equation (5.6) is used to evaluate possible solutions of pan stage schedule cycle times. These solutions are results from the pan stage steady state flow model with adapted inputs of the pan cycle time duration. The value of the premium sugar bonus, **B** is determined by the function presented in Figure 23.

Steam quantity, premium sugar bonus, product sugar quantity and product molasses quantity results from the adapted pan stage steady state flow model are used as contributing components in determining an optimal scheduling solution. The other primary model inputs are the default local model parameters as discussed in Section 5.2.2 and the average syrup production rate from the model presented in Section 5.2.1. The primary model outputs are seed pan footing quantities, swing pan duties, pan steam rates and strike start and completion times. The model interaction between these components is presented in Figure 24.

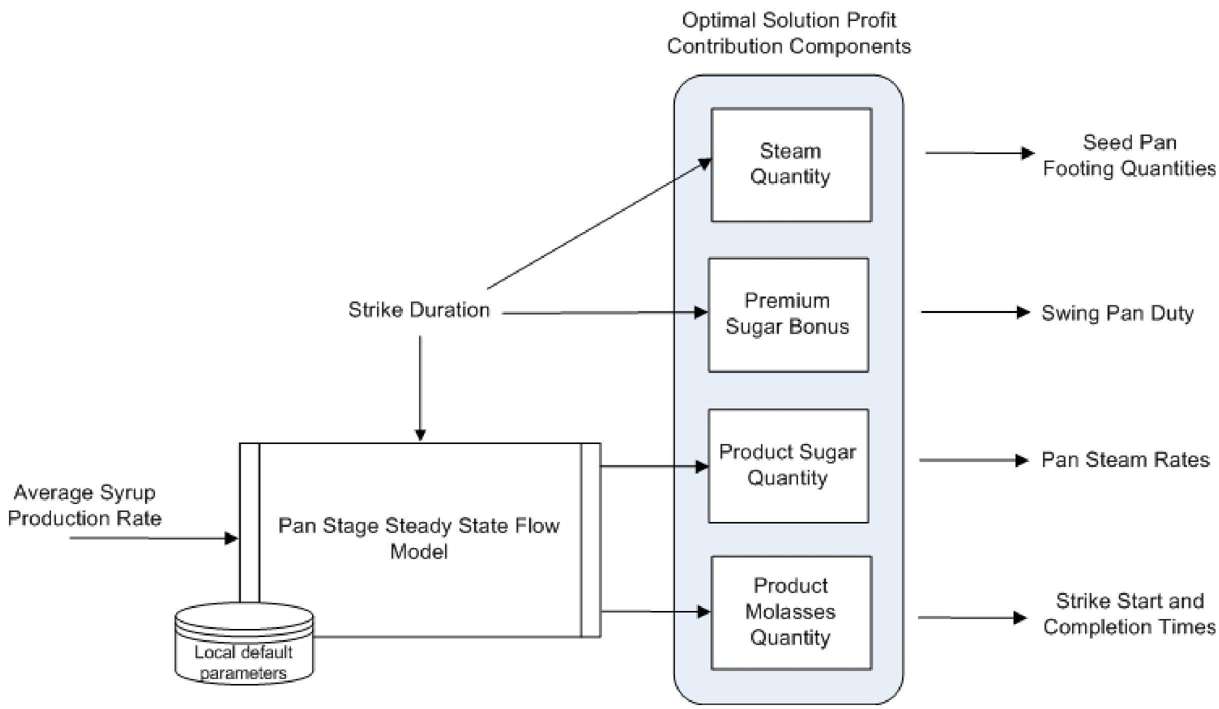

Figure 24: Schedule optimisation model utilising the pan stage steady state flow model

The schedule optimisation algorithm is based upon the vacuum pan phase detection and forecast algorithm from Section 5.2.4 and the steady state pan stage flow model from Section 5.2.2. Iteratively cycle times based across the schedule cycle time of Figure 23 are used as the functional inputs during for the steady state flow model. Flow model results are evaluated using Equation (5.6). The solution obtaining the maximum profit value is then used to establish the designated model outputs.

An alternative schedule is inferred upon the completion of the current high grade seed pan cycle and then branching to pan duties as defined by Figure 22. The vacuum pan phase detection and forecast algorithm from Section 5.2.4 are used to establish the current point in operational phase of the high grade seed pan and the current drop point forecast. From this information and the defined cycle time the new schedule is established and the start and completion points of each pans in the schedule is calculated. Optimal swing pan duties are calculated upon this basis and the pan steam rates, based upon the scheduled strike duration, are used with the seed pan footing value calculated from the average seed pan flow rates taken from the adapted pan stage steady state flow model.

5.3 Fundamental System Supporting Technologies

Several supporting technologies have been developed specifically to support the overall software infrastructure. These features are fundamental to the success of the KBSSS and are pivotal to the successful implementation of the process models and their ability to integrate within the KBSSS. These technologies were designed and developed specifically as core supporting functions for the software engines of the KBSSS.

A time based methodology is employed for mapping forecast production quantities/consumption rates and apportioning them to future time intervals. This technique is a fundamental and core component of the KBSSS that acts cooperatively with the process models to provide forecast capabilities and addresses the limitation identified in Section 2.6.1 in the provision of a time based horizon for predictive models. The developed system is innovative, unique and developed specifically for supporting the dynamic interrelational pan stage process models.

A blackboard system has also been designed and implemented for information exchange between the KBSSS major subsystem. This allows the storage and retrieval of numeric based information pertaining to each of the major software engines through the use of a database solution for data storage. As part of this system, a blackboard scheduler is responsible for the execution order of the KBSSS subsystems interactions with the blackboard.

These two features are of fundamental importance to the KBSSS and are discussed in the following sub-sections.

5.3.1 Dynamic Allocation for Forecast Quantities Algorithm

The dynamic allocation algorithm was initially established as part of background supporting technology for the syrup prediction model however supports several other dynamic interrelational pan stage process models as established later in this section. The following section proposes a unique and innovative dynamic allocation algorithm for use as a prediction mechanism to allocate forecast quantities over a prediction horizon. This section references the syrup prediction problem in presenting the development and the application of the dynamic allocation algorithm.

The syrup prediction model, as established in research by the author (Dodd, Broadfoot, Yu and Chiou, 2005a), predicts the future syrup loading quantities to the pan stage by relating cane receival data with juice processing information through use of an empirical factory operational fraction. This measure determines the fractional sucrose and impurity losses through bagasse and mud by-products and consequently the sucrose and impurity quantity loadings in syrup to the pan stage. Collectively this determines future syrup quantities loadings to the pan stage and allows a forward forecast of the future pan stage loading of syrup.

This model is of key importance as syrup comprises the basic input to the pan stage with direct feed to the pan stage liquor tank. Given that there is approximately a 96 minute delay from cane entering the factory and being processed to its associated syrup flows to the pan stage, this provides the prediction window for future syrup quantities flowing to the pan stage based upon cane receival crushing information.

It is important to realize that cane receival information is non-discrete and may be entered into the sugar mill cane receival system at any time. There may also be subsequent delays till information for the first expressed juice sample is available from the juice laboratory. These information sources need to be collated together for each rake of cane to allow an estimate of the sucrose quantity in syrup produced from the juice to be calculated.

The processing duration to crush a rake of cane will differ between rakes depending upon the number of bins in the rake and the transport system at the factory. For smaller factories that receive cane through lorry delivery the cane tipped per bin is about 6 minutes of crushing time. For factories with tramway systems no juice sample is used to analyse the cane unless there are at least three to four bins, each with an approximate weight of 4 tonnes. Hence this could equate to 16 tonnes of cane to be crushed. In a large factory this may correspond to only 1 or 2 minutes of crushing. The typical range of rakes correspond to 10 to 30 minutes of crushing but this is solely dependant upon the number of bins within the rake, factory crushing rate and cane delivery system in place.

Such varying factors bring about a challenge to the development of a forward prediction model for relating syrup quantities to the pan stage from cane quantities being crushed and in allocating these syrup quantities to future forecast intervals over the prediction horizon.

In order to realize a predictive model for the allocation of quantities to future time intervals an innovative dynamic forecasting algorithm was developed specifically to overcome the previously detailed problems. This method is tightly integrated into and works in tandem with the pan stage process models to provide forecast abilities.

Given a specified forecast period for forward prediction at 15 minute intervals, the forecasting algorithm determines and apportions the sucrose and impurity quantities for each batch of cane to the associated prediction intervals over the forecast horizon. Determining the exact intervals that these quantities are apportioned to and the apportioned quantities forms the overall goal of the proposed algorithm.

Key requirements in the development of the dynamic allocation process are the:

- determination of projected starting and finishing points for future batch processing accounting for process delays;
- ability to handle date/time points for any period in the day;
- robust handling of date/time for rollover periods across the midnight period of the day;
- number of batches to be processed is not initially known so the algorithm must be generic enough to handle an undefined amount;
- batches can exhibit differing processing rates so starting time information for batches may differ;
- forecast horizon must be flexible;
- forecast interval resolution fixed to 15 minutes discrete phases; and
- software components are reusable and able to be applied to other forward forecast process models for the pan stage.

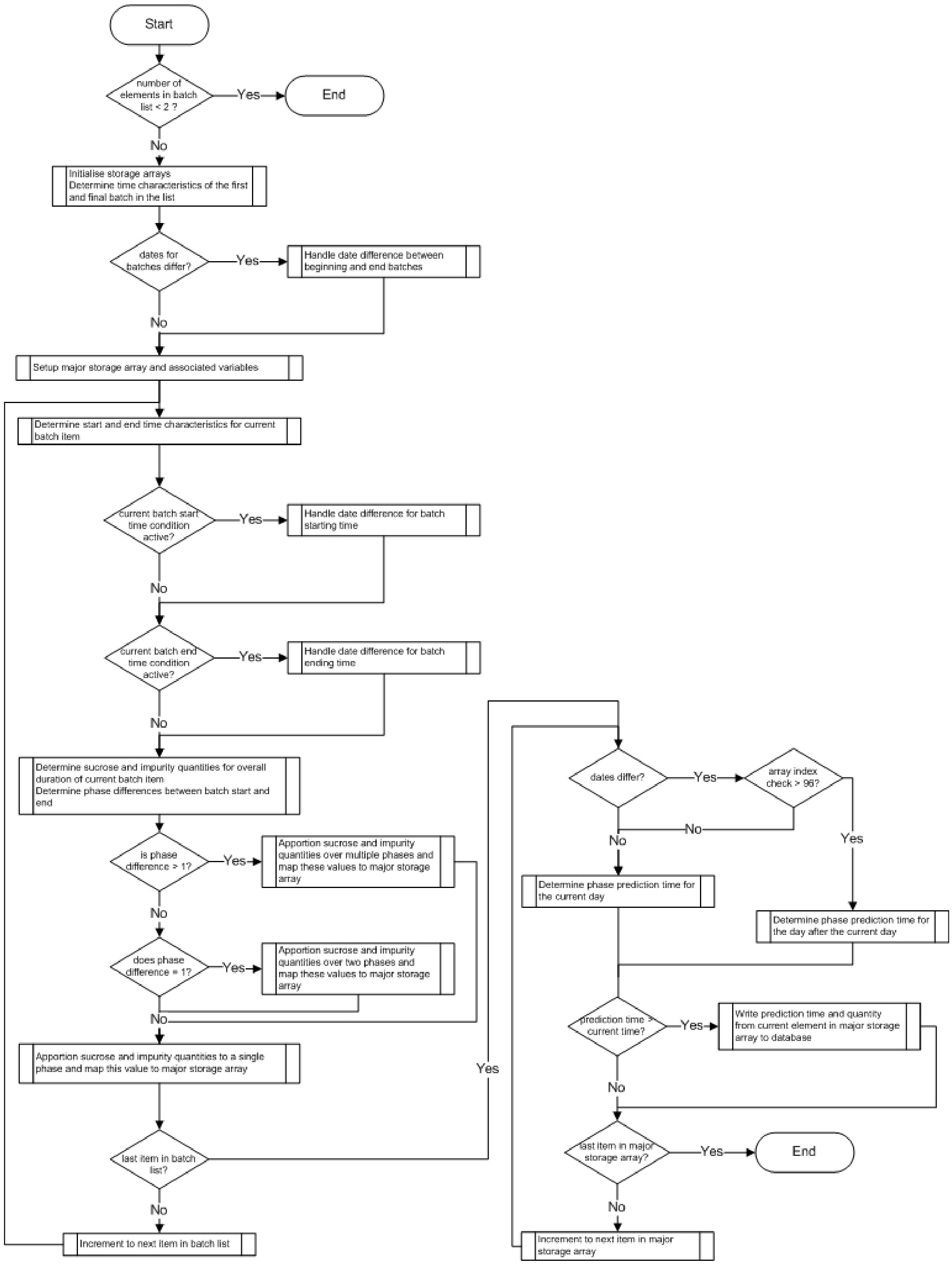

Figure 25: Dynamic allocation algorithm used to allocate predicted quantities to future forecast intervals

The overall algorithm as depicted in Figure 25 consists of two major event loops. The first event loop progressively moves through each batch in a list and determines to which 15 minute phase in the day that the start and end batch belong to. The overall quantity for the batch is determined by the sucrose and impurity model (Dodd, Broadfoot, Yu and Chiou, 2005a). This batch quantity is linearly apportioned to each phase dependant upon how many minutes of the overall duration occur within each phase. The difference between the batch start and end phase numbers is used as the basis for allocating quantities to the intervals occurring between the start and the end of the batch. With no difference, quantities are allocated to a single phase. If a large difference exists then the quantities are apportioned over a greater time period and allocated to multiple phases. The overall batch is temporarily broken down into a series of phases which store the allotted quantity information. Each element in the individual batch array is then mapped back to the major data array for storage. This process is depicted in Figure 26.

In this manner the algorithm iterates through each batch in the list, determines the number of required phases and quantities for each phase. Each phase is then mapped to the overall phase data for the day. A day period consists of 96 discrete 15 minute phases – however this mapping only needs to be started from the initial phase number of the very first batch. The initial phase number for the start of the first batch is stored for compact data representation and used as an offset for array access. Further date/time accountability is ensured by extending the array beyond this 96 phase “soft limit” if a batch start or end period, encountered throughout the iterative process, moves into a new day. This is only performed for the allocation of syrup quantities with prediction intervals that cross the midnight threshold into a new day period.

Figure 26 shows the updating and mapping process used to translate quantities allocated in individual phases to the overall data array. Several batches may update quantities to a particular phase interval and act in an additive fashion to existing array data. While the majority of syrup quantities for a cane rake will only be allocated to a single or two time intervals, the approach is robust and flexible enough to handle cane rakes of a much larger processing duration and will allocate them appropriately.

The second event loop in the algorithm progressively passes through each element in the major data array and determines the actual prediction time that the array element corresponds to. This determination is provided by ancillary information from the initial setup of the major data array. Final results are then written to the blackboard system for further use in the liquor stock tank model and steady state flow model.

Given that this proposed algorithm deals with assigning quantities of materials to future forecast intervals this methodology, with some minor modification to handle process delays and the method used to determine projected quantities to be apportioned during batch processing, is also used for:

- Forward prediction of syrup usage during forecast batch pan operational phases.
- Forward prediction of A molasses usage during forecast batch pan operational phases.

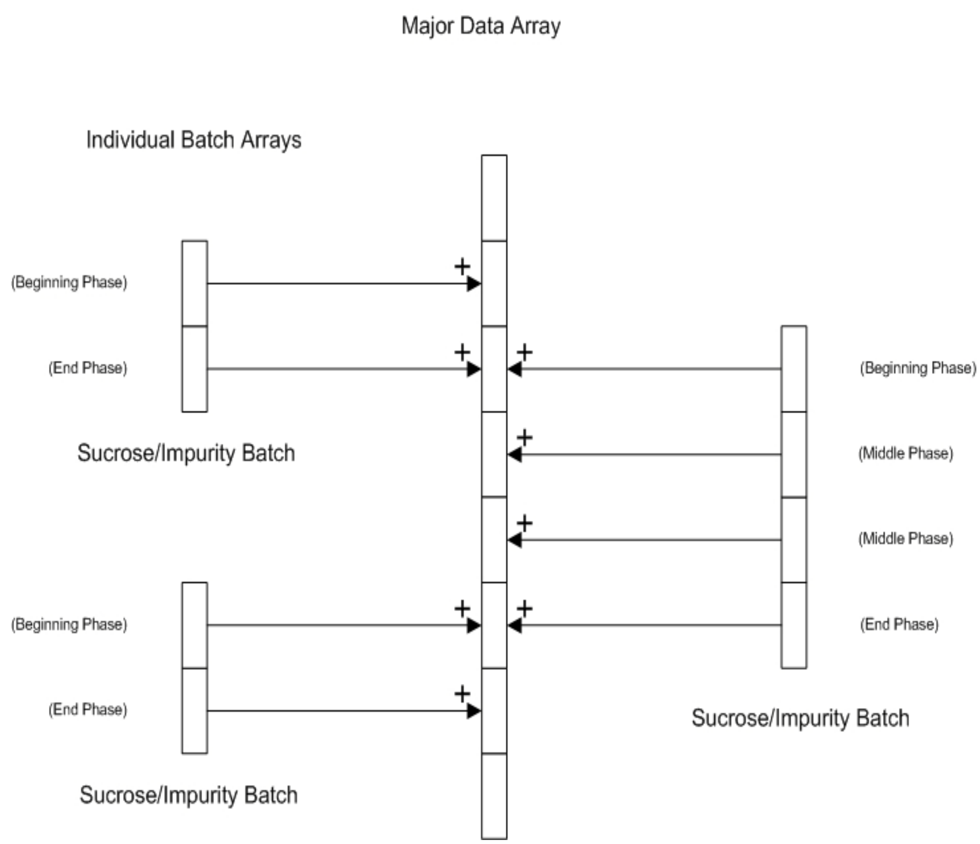

Figure 26: Updating of major data array with quantities from individual batch array phases corresponding to the processing of sucrose/impurity batches.

- Forward prediction of B molasses usage during forecast batch pan operational phases.

- A molasses return rates from centrifugals after A massecuite pan drop to receiver.

- B molasses return rates from centrifugals after B massecuite pan drop to receiver.

Furthermore, this approach facilitates a unification method for batch and continuous processing regimes in the prediction of feed and production rates of process materials. This methodology makes it easy to integrate continuous processing streams. For each time interval continuous process flow rates and hence quantities are fixed. The only modification required is to locate the interval period relevant to the continuous flows and perform the required quantity updates in an additive manner. Since the time intervals are readily available over the forecast period this is a simple process to interrogate the future time interval forecast list and update the associated quantities. The structured methodology presented makes seamless unification of batch and continuous processing possible when forward predicting process stream feed or production rates.

5.3.2 Blackboard System

A blackboard system is utilised to store results from the major subsystems while the system builds a forward forecast of operating conditions, system advice and recommendations and justifications. Given the variety of knowledge sources used to carry out the overall forward prediction, the blackboard system is used to incrementally build a solution over the forecast period and work towards providing the prediction. The blackboard system, as an information storage repository, holds all major results for each completed run of the process models and acts as the intermediary for the fuzzy inference engine to interact with. At each prediction point the KBSSS builds a forward prediction and stores the value of each major process variable for each forecast point across the forecast period. This information is not only stored for information exchange between the subsystem models and access between the pan stage process models but also to allow review of archived data from previous forecasts. This is important to aid in performance reviews of the major system components through retrospective inspection.

Logically the blackboard storage structure representation appears in Figure 27. At each prediction point a series of data values are determined through use of the dynamic industrial process models working in tandem with the fuzzy rule base to generate a prediction of future pan stage operating conditions over the forecast period. The forecast period is broken down into a series of discrete predefined intervals over this forecast horizon and process variables tracked at each of these points. Successive predictions *p* build up a series of prediction matrices consisting of variables *v* stored at each forecast interval *t.*

The blackboard system implementation uses a relational database to store the information from the KBSSS knowledge sources. The retrieval/insertion of objects within this blackboard structure are performed using retrieval/insertion methods as supported in previous research (Corkill, Gallagher and Johnson, 1987) in order to affect efficient and consistent blackboard interaction. Standard SQL queries are used for the insertion and querying of information sources within the blackboard system.

Implementation-wise the underlying database uses the logical structure, presented in Figure 27, and maps this to a predefined database table structure. The tuple representing a row in the blackboard database is:

{KnowledgeSource, VariableName, ForecastTime, PredictionTime, VariableValue}

where,

KnowledgeSource *is the name of the knowledge source contributing the data,*

VariableName *is the name of the variable that data is being stored against,*

ForecastTime *is a date/time paired data value representing a forecast interval within the forecast period,*

PredictionTime *is a date/time paired data value representing the time that the forecast was generated,*

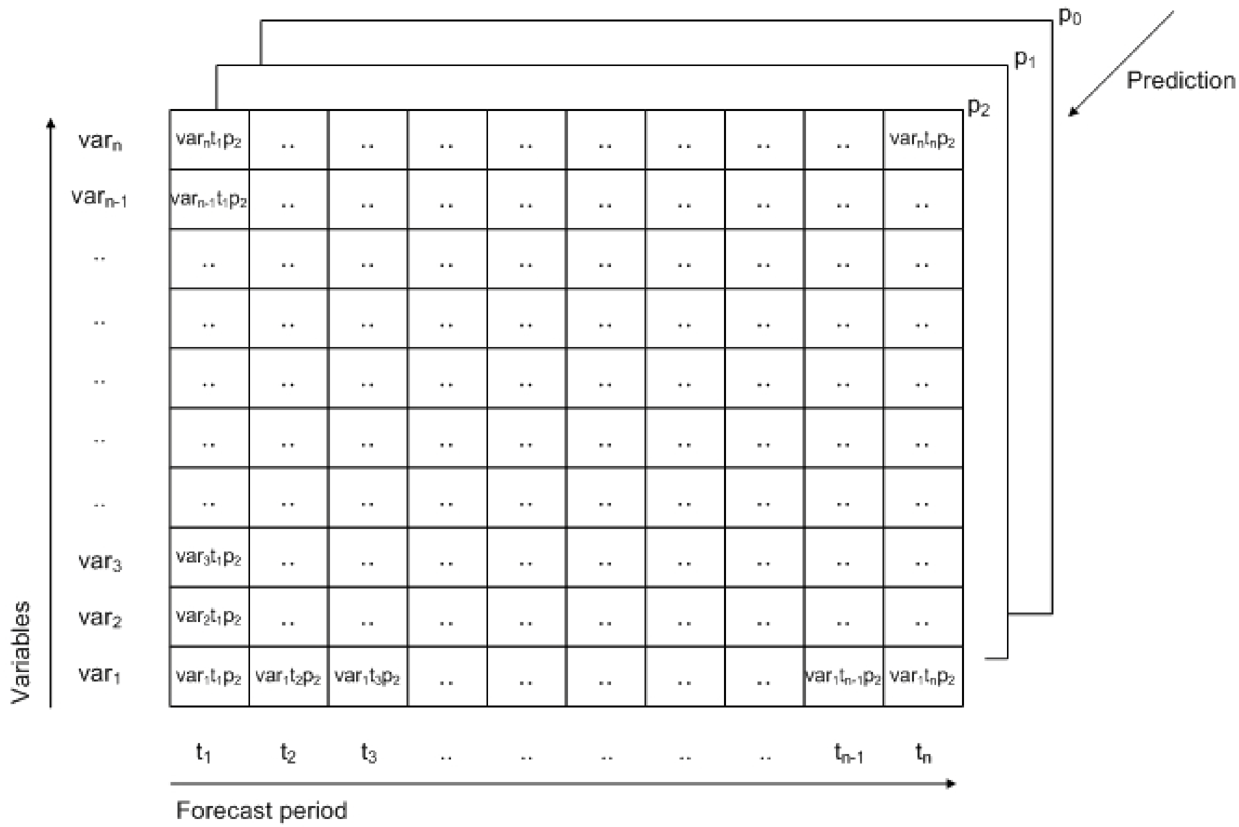

Figure 27: Blackboard system component implementation

VariableValue *is the actual data value stored.*

This compact representation allows flexible information storage for knowledge sources with varying forecast periods. For example, Section 5.2.1 details the syrup prediction model being restricted to a 96 minute forecast period which forms the operational prediction boundary on this particular pan stage process model.

A blackboard scheduling system controls the sequence for interaction of the fuzzy inference engine and the pan stage process models and with blackboard. Due to logical data flow from these operations, the blackboard scheduling system also schedules the discourse and explanatory integrator subsystem processing. A predetermined scheduling action is required due to the data dependencies that exist both within the models and the inference process. An information hierarchy exists within the process models determining the order of their processing. Figure 28 shows the pan stage process model hierarchy. Pan stage process models higher in the hierarchy are dependant upon information from the more fundamental models at the lower levels. The arrows in the diagram display information

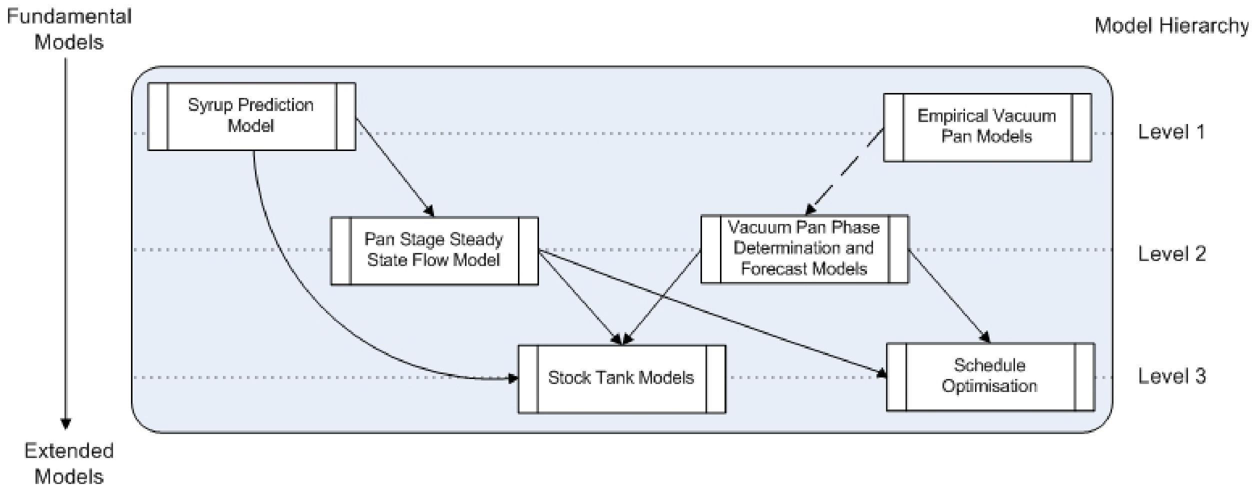

Figure 28: Model hierarchy for blackboard scheduling

flow between the process models. The empirical vacuum pan models, as one of the essential and key developed pan stage process models, do not take part in scheduling by the blackboard scheduling system. The empirical vacuum pan models are static in nature and are used as local process model parameters for vacuum pan phase determination and forecast models. This relationship is in Figure 28 indicated by the broken arrow.

At the most significant hierarchical level 3, the schedule optimisation model utilises the pan stage steady state flow model and vacuum phase determination and forecast process model. This use is through direct interaction with components blackboard results from the pan stage process models and the use of the actual models themselves.

Models are iteratively processed based upon level within the defined hierarchy. Lower level models are scheduled for completion first with the next level of models in the hierarchy successively scheduled after their completion consecutively. Due to the dependence between local trend adjustment through the fuzzy inference process and also the process of generation of explanations to support system advice, the pan stage process models require additional information processing to be performed in one atomic transaction. This relationship is presented in Figure 29 with the blackboard system scheduler in charge of directing the subsystem components displayed in the shaded area. Annotated numbers within the figure refer directly to the order of processing steps for pan stage process model evaluation working in tandem with the fuzzy rules base and the KBSSS explanatory system.

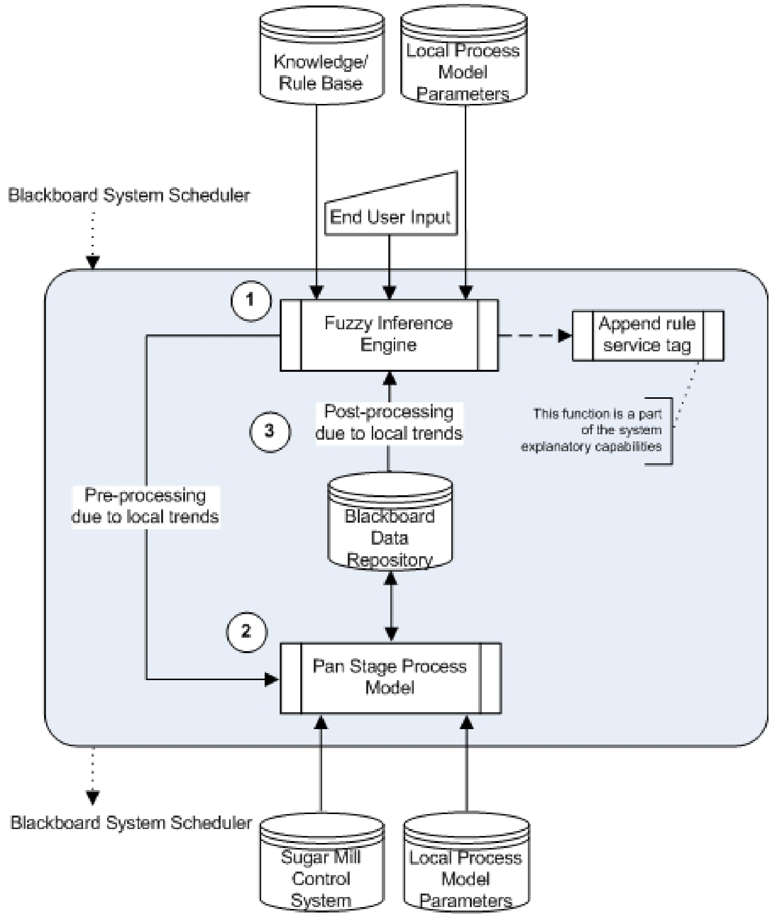

Figure 29: Blackboard system scheduling with simplified subsystem data interaction for pan stage process model processing

These steps are:

1. Pre-processing adjustment of pan stage process model parameters due to localised conditions. As part of the fuzzy inference process the explanations tagged to rules are stored for later collation and presentation by the discourse and explanation integration subsystem (detailed in Section 5.5). This step of the process draws from the fuzzy knowledge and rule base, end user input and local model parameters for the process model under processing.

2. Pan stage process model evaluation. The fuzzy inference process adapts local process model parameters. These adapted parameters are combined with the default model parameters as detailed in Section 5.4. This localisation allows adaption to current real world operating conditions that are unknown to the KBSSS until runtime. Results from the pan stage process model are stored within the

blackboard data repository for further use in the fuzzy inference process and by process models further up the model hierarchy.

3. Post-processing adjustment of pan stage process model results. Post-processing of the pan stage process model results occurs to also provide a match with local operating conditions. Explanations tagged to these rules further assists in the justification process of system advice and recommendations.

The blackboard scheduling system iterates through each of the pan stage process models as defined by the hierarchy in Figure 28 with the information processing order for fuzzy inference engine pre-processing and post-processing of rules working in tandem with rule tagging, for explanations, and evaluations of the process models as dictated by Figure 29. As a final event in the schedulers role, it calls the discourse and explanatory integrator subsystem for collating and formatting supporting justifications as presented in Figure 10. This entire iterative regime is repeated each time the KBSSS performs a forecast of future operating conditions and its generation of system advice and recommendations with supporting justifications.

The following section further describes in further detail on the method used to integrate the pan stage process models with the fuzzy rule base.

5.4 Integration of Process Models into the Fuzzy Rule Base

The fuzzy inference engine is a core subsystem of the KBSSS as presented in Chapter 4. This system processes user responses against the systems knowledgebase to produce system recommendations and advice. The operation of this subsystem is based upon conventional fuzzy If-Then rule based systems mechanics. To ensure refinement of its advice and in matching against real world conditions, that do not form part of the static predefined knowledgebase, the system must be able to provide adjustment to match local operating conditions. In the provision of this capability, techniques for the merger of the dynamic pan stage industrial process models with the fuzzy rule base are proposed in the following section.

In overcoming the limitation of existing approaches presented in Chapter 2, this method allows the:

- prediction of future pan stage operating conditions based upon approximate information;
- inclusion of heuristic based information to support real world operating conditions based upon current operating circumstances and localised trends;
- adaption of localised parameters without the need for modification of the pan stage industrial process models; and
- functioning of pan stage process models in the absence of user supplied local trend information.

The following subsections review the fuzzy If-Then rules in relation to the KBSSS implementation. This is then followed by the method for pan stage process model integration within the fuzzy rule base and methodology in providing a prediction of future pan stage operating conditions.

5.4.1 Fuzzy Linguistic Variables

Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, fuzzy logic incorporates an alternative way of thinking. Such modelling of complex systems using fuzzy logic utilizes a higher level of abstraction that originates from knowledge and experience. Fuzzy logic allows for the expressing of imprecise knowledge with linguistic descriptions such as *very long*, *high temperature*, and *low yield*.

This approach is based upon seminal research first presented by Zadeh (1965) in the development of fuzzy set theory. For example, the fuzzy linguistic variable *level* representing the process material quantities in a stock tank may be represented as in Figure 30. The linguistic values *of empty, low, mid, high* and *full* that the fuzzy variable may take are each represented by a membership function. A stock tank holding a quantity of 63 tonnes of process material would have a degree of fulfilment (Berkan and Trubatch, 1997) of 0.23 for the *empty* fuzzy set and a degree of fulfilment of 0.77 for the *low* fuzzy set.

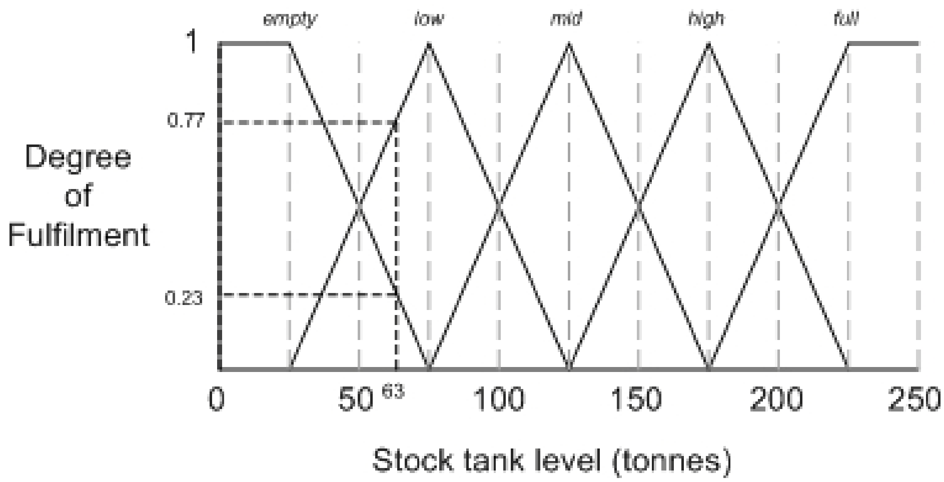

Figure 30: Fuzzy membership functions for the fuzzy variable level representing quantity of process material in a stock tank

This modelling approach allows for approximate information such as human experience and knowledge to be encoded as part of knowledge representation and provides a powerful framework for information modelling of imprecise concepts.

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This modelling approach allows for approximate information such as human experience and knowledge to be encoded as part of knowledge representation and provides a powerful framework for information modelling of imprecise concepts.

5.4.2 Fuzzy If-Then Rules

Fuzzy If-Then rules provide a mapping functionality for domain knowledge between fuzzy sets that exist in a relationship. This allows associations to be developed between fuzzy neighbourhoods within a region. The modelling capabilities afforded by this approach allow the capturing of inexact information which comprises human knowledge.

The standard fuzzy rule is of the form:

IF *x* is *A* **THEN** *y* is *B* (5.7)

where,

x *is the linguistic variable of the rule antecedent,*

A *is the linguistic value of the rule antecedent,*

y *is the linguistic variable of the rule consequent,*

B *is the linguistic value of the rule consequent.*

Each of the fuzzy values represented for the fuzzy rules in (5.7) is composed of a membership function as detailed in the previous subsection. The left hand side component of this rule is known as the antecedent and the right hand side is known as the consequent. An example of human knowledge for the pan stage process may be the following relationship:

IF *fugal wait time* is *high* **THEN** *duration till receiver is fugalled* is *long*

This fuzzy rule is depicted visually in Figure 31. The fuzzy antecedent variable *fugal wait time* is mapped against the fuzzy consequent variable *duration till receiver is fugalled*. Fuzzy values within the diagram occupy regions and allow associations to be established as highlighted by the connecting arrows.

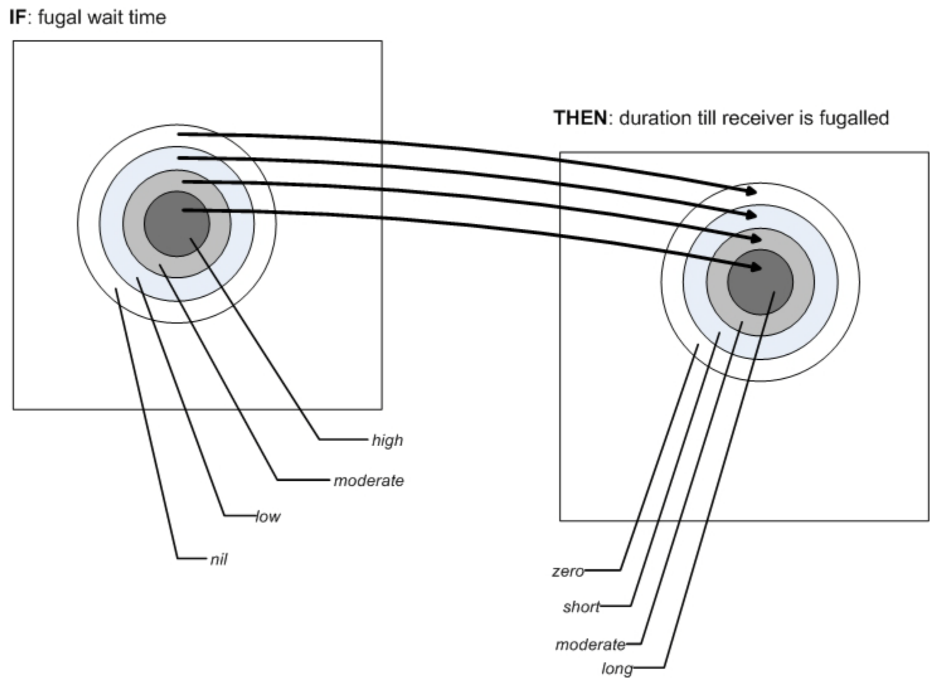

Figure 31: Fuzzy rule relationship displaying antecedent mappings to associated consequent components

5.4.3 Method of Integration for Process Models with Fuzzy If-Then Rules

This section covers the approach used in the implementation and merger between the dynamic industrial pan stage process models and the fuzzy logic rules for use in the prediction process. This implementation and integrationary approach will be explained using process diagrams together with functional definitions of the fuzzy process. The following sections will present an overview of the approach used for fuzzy logic based pre-processing and post-processing adjustments for pan stage process model input parameters and output data respectively given. A summary of the integration process is then provided.

Previous research (Takagi and Sugeno, 1985) has proposed the approximate modelling of complex systems through approximations of the behaviour of smaller segments of the solution. A sub class of this approach is the zero-order Sugeno fuzzy model having fuzzy rules of the following form:

IF x is A **THEN** y = b (5.8)

where,

***x** is the input value from the system consultation process,*

***A** is the linguistic value of the rule antecedent,*

***y** is the output,*

***b** is the fuzzy singleton membership function value.*

In following the zero-order Sugeno fuzzy model approach of Equation (5.8) the fuzzy singleton representation is used for consequent membership functions representation due to ease of dynamically allocating the process model numeric results. This representation also allows pan stage process model input parameters to be statically specified as consequent fuzzy singletons.

The fuzzy rule format from (5.8) is modified to:

IF (user input:variable value) is (linguistic value)

THEN (process model:parameter variable) = (constant value) (5.9)

IF (user input:variable value) is (linguistic value)

THEN (output variable) = (process model:output value * constant value) (5.10)

where,

***user input:variable value** is the value determined through the user consultation process and reflects real world information that is not part of the predefined system knowledge base,*

process model:variable value *is a defined data variable for a pan stage process model,*

***linguistic value** corresponds to a particular fuzzy value for a given fussy set,*

constant value *is a predefined static numeric value,*

output variable *is the resulting storage parameter for the results of the fuzzy inference process.*

Equation (5.9) and Equation (5.10) are derived from Equation (5.8) to allow for the incorporation of the pan stage process model into the fuzzy rule base. The defined pan stage process models now becomes part of the expert system rule and is chained into the fuzzy rule antecedent and consequent components. The components comprising the consequent function represent the functional value of the fuzzy singleton membership function location in the consequent fuzzy set universe of discourse. This approach assigns the fuzzy singleton membership function value from the results of a pan stage process model through a simple lookup process. This results in a tightly bound relationship between the fuzzy rule consequent function component of Equation (5.8) and the pan stage process model.

The fuzzy singleton membership function for fuzzy rule consequents is presented in Figure 32. This function is characterised by a degree of fulfilment of unity at one particular universe of discourse point and zero for all others. Related research into dynamic singleton membership function adaption was undertaken by the author for fuzzy system control based upon neural network learning (Dodd, 2007). However in the KBSSS implementation singleton adaption is due to user supplied information, from the consultation process, to match against real world operating conditions. The uniqueness of the approach is in integrating the meta-knowledge adaption (Chiou and Yu, 2007c) with the proposed pan stage process models and fuzzy rule singleton consequent functionality from the zero-order Sugeno model approach.

The final crisp defuzzified output value is determined by the commonly accepted weighted average value method for the fuzzy rules according to (5.11) :

$$y' = \frac{\sum_{i=1}^{N} DOF_i y_i}{\sum_{i=1}^{N} DOF_i} \tag{5.11}$$

For each rule i having a consequent output value of y_i with an rule antecedent degree of fulfilment value of DOF_i then the final defuzzified output value, for a system with N fuzzy rules, is y'. This defuzzification process converts the singleton rule consequents into one crisp output depending upon rule firing strengths from the inference process.

5.4.3.1 Fuzzy Pre-processing

Fuzzy logic is used as the pre-processor for pan stage process models input parameters in providing localised to suit real world operating conditions that are not part of the predefined static KBSSS knowledge base. The inference process is carried out from information elicited from end user queries working in conjunction with the fuzzy knowledge base to adapt pan stage process model parameters to suit localised data trends for real world operating conditions. The functional definition for this process working in tandem with the fuzzy inference process is:

PreprocessingFuzzyRule($Datasource_{KnowledgeBase}$: $q_1, q_2 .... q_m$,

$Datasource_{ModelParameters}$: $p_1, p_2 .... p_n$)

= ($Output_{ModelParameters}$: $p_{1'}, p_{2'} .... p_{n'}$)

Within this functional definition $q_1, q_2 .... q_m$ are the submitted end user responses from the consultation process inferred against the knowledge base data source, $Datasource_{KnowledgeBase}$ and provides localised adaption of the model parameters, $p_1, p_2 .... p_n$, from local KBSSS pan stage process model data sources. The return values of **PreprocessingFuzzyRule** are the parameters $p_{1'}, p_{2'} .... p_{n'}$ corresponding to pan stage

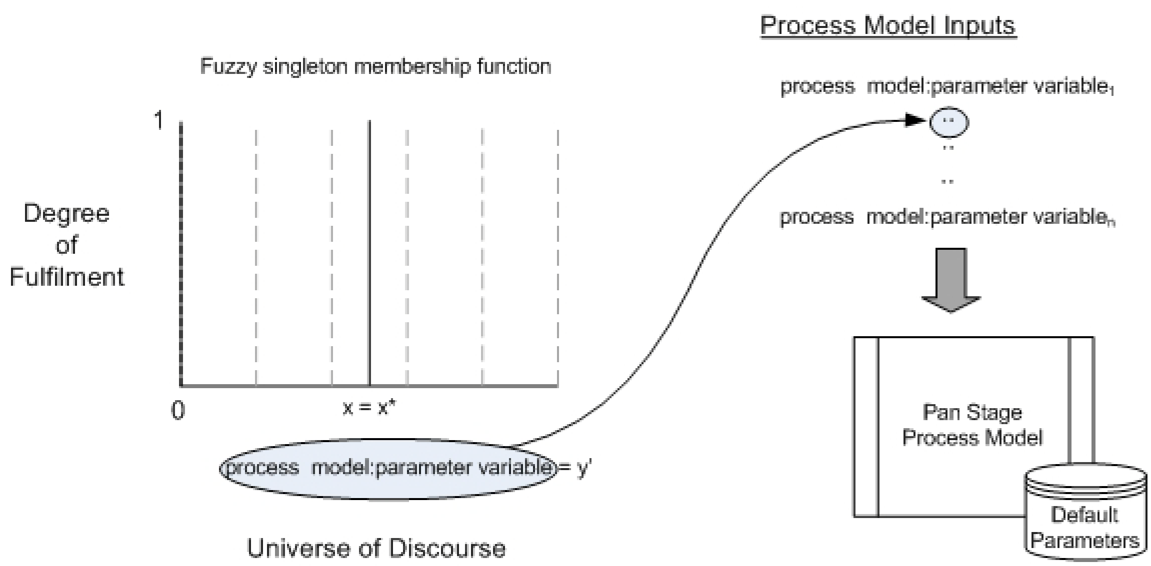

Figure 32: Relationship between fuzzy consequent membership functions and pan stage process model inputs

process model parameters. These results are a localised variation of the original default model parameters having being adapted to match real world operating conditions.

Fuzzy rules for the pre-processing process follow the format presented in Equation (5.9). After the fuzzy inference process (Berkan and Trubatch, 1997; Cox, 1999) has been undertaken by the KBSSS, the defuzzification process from Equation (5.11) is performed to resolve the rule firing strengths in combination with the fuzzy rule consequent singleton membership function values into a single crisp output. This output then forms one of the major inputs to the pan stage process models. This process is depicted in Figure 32.

5.4.3.2 Pan Stage Process Model Forecast

After the pre-processing adaption is performed, the proposed pan stage process models detailed in Section 5.2, are run to provide a forward forecast of future pan stage operating conditions.

The functional definition for this process working in tandem with results from fuzzy pre-processing method detailed in the previous section is:

ProcessModel ($Datasource_{Blackboard}$: $b_1, b_2 .... b_m$,

$Datasource_{ModelParameters}$: $p_{1'}\, \boldsymbol{\Phi}\, p_1, p_{2'}\, \boldsymbol{\Phi}\, p_2 .... p_{n'} \boldsymbol{\Phi}\, p_{n,}$

$Datasource_{ControlSystem}$: $c_1, c_2 .... c_{k)}$

= ($Datasource_{Blackboard}$: $o_1, o_2 .... o_p$)

Within this functional definition $b_1, b_2 .... b_m$ are the data dependencies from other pan stage process models and drawn from the blackboard system data source $Datasource_{Blackboard}$. Outputs from pan stage process models can be fed forward to process models further down the hierarchy as depicted in Figure 28. Information sources are retrieved from the KBSSS blackboard system. Recall from Section 5.3.2 that the blackboard system is used as an information repository for working results from the pan stage process models and works as an intermediary for interaction between the proposed pan stage process models.

Control system data $c_1, c_2.... c_k$ is drawn from a parasitic data feed to existing control system data source $Datasource_{ControlSystem}$ as depicted in Figure 3. The information sources required is particular to the individual pan stage process model and has been outlined in Section 5.2.

The process model local default parameters, $p_1, p_2.... p_n$, are drawn from the model data source, $Datasource_{ModelParameters}$, are aggregated with the results $p_{1'}, p_{2'}.... p_{n'}$ of the fuzzy pre-processing source $Output_{ModelParameters}$ outlined in the previous section. Default parameters have lower precedence and are always overridden by their fuzzy logic derived counterparts – the results of the pre-processing operation are used instead. An aggregation operator **Φ** is used which provides this precedence. For each of the required pan stage process model input parameters this aggregation method is used.

Although fuzzy logic is robust and able to deal with imprecise data, fuzzy logic is unable to function in the event of missing data (Berkan and Trubatch, 1997; Cox, 1999) required for the inference process. Due to the method used in merging the fuzzy logic rule base with the dynamic pan stage process models, in the absence of fuzzy inference localised adaption for process model input and output, the system will function though the use of default parameters for the process models. However local model parameters have lowest precedence and are always overridden. Use of the default process model parameters will yield a generic process model without localisation capabilities accounting for current operational conditions. This approach ensures continued system functioning in absence of the fuzzy pre-processing of parameters.

The values returned from **ProcessModel** are the parameters $o_1, o_2.... o_p$ corresponding to pan stage process model output values as a result of running the proposed models are then stored against the blackboard data source, $Datasource_{Blackboard}$. These values are then available for fuzzy post-processing adjustment to provide localised adaption of results in order to suit real world conditions that are not part of the predefined knowledge base.

5.4.3.3 Fuzzy Post-processing

Outputs from the pan stage process models can be adapted to suit localised conditions in a similar process to that occurring in the pre-processing phase. Fuzzy logic is used as the post-processing adjustment for pan stage process models output values to provide localised adaption to suit real world operating conditions that are not part of the predefined static KBSSS knowledge base.

The inference process is carried out from information elicited from end user queries working in conjunction with the fuzzy knowledge base to adapt pan stage process model output data to suit localised data trends for real world operating conditions. The functional definition for this process working in tandem with the fuzzy inference process is:

$$\textbf{PostProcessingFuzzyRule}(Datasource_{KnowledgeBase}: q_1, q_2 .... q_m, \quad Datasource_{Blackboard}: o_1, o_2 .... o_p)$$

$$= (\text{Output}_{\text{variables}}: \text{o}_{1'}, \text{o}_{2'} .... \text{o}_{\text{p}'})$$

Within this functional definition $q_1, q_2 .... q_m$ are the submitted end user responses from the consultation process inferred against the knowledge base data source, $Datasource_{KnowledgeBase}$ and provides localised adaption of the process model output values, $o_1, o_2 .... o_p$, from local KBSSS pan stage process model data sources. The return values of **PostProcessingFuzzyRule** are the parameters, $\text{o}_{1'}, \text{o}_{2'} .... \text{o}_{\text{p}'}$, corresponding to pan stage process model output variable values. These results are a localised variation of the original pan stage process model output data, $o_1, o_2 .... o_p$, stored in the blackboard system data repository, $Datasource_{Blackboard}$.

When compared to the pre-processing phase, the minor difference is that pan stage process models results are chained into the fuzzy If-Then rule consequent component with the location of the singleton membership function dynamically scaling due to the affects of the output function of the rule consequent component. Fuzzy rules for the post-processing process follow the format presented in Equation (5.10). Process model results are used to assist in dynamically allocating the fuzzy singleton membership function location defined by the fuzzy rule consequent component. For the KBSSS, simple scaling adjustment of the pan stage process model output as part of the fuzzy If-Then rule consequent output function suits the application requirements.

Similar to the pre-processing phase, after the fuzzy inference process (Berkan and Trubatch, 1997; Cox 1999) has been undertaken by the KBSSS, the defuzzification process from Equation (5.11) is performed to resolve the rule firing strengths in combination with

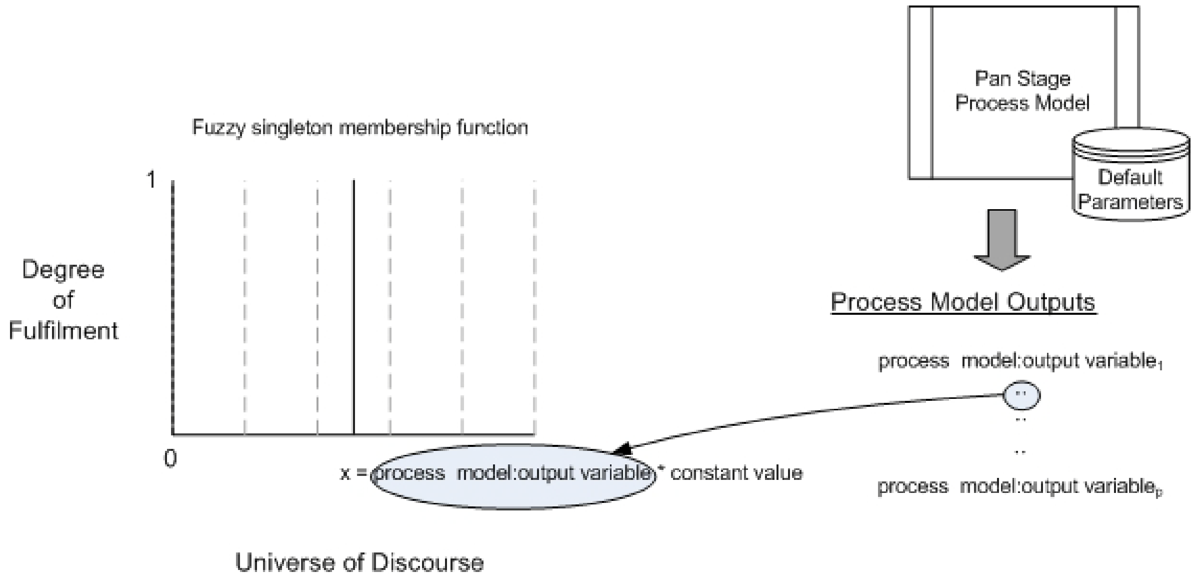

Figure 33: Relationship between fuzzy consequent membership functions and pan stage process model outputs

the fuzzy rule consequent singleton membership function values and defined consequent constant values into a single crisp output. This resulting output then forms the final output for the process model output under consideration. This process is depicted in Figure 33.

The aggregation operation used for pre-processing is similarly used as part of the collation of result post-processing. The results of the pan stage process model, $o_1, o_2 .... o_p$, are then combined through the use of the aggregation operator **Φ** with the possible post-processing crisp defuzzified values, $o_{1'}, o_{2'} .... o_{p'}$. Post-processing results have precedence over the pan stage process model direct output. This results in the final output stored to the blackboard system information repository, $\text{Datasource}_{\text{Blackboard}}$. This results in final stored output of:

$\text{Datasource}_{\text{Blackboard}}$: $o_{1'}\,\mathbf{\Phi}\,o_1,\ o_{2'}\,\mathbf{\Phi}\,o_2 ....\ o_{p'}\mathbf{\Phi}\,o_p$

This final resulting output is stored as part of the blackboard system data sources and available to other models in the hierarchy presented in Figure 28. Recall from Section 5.3.2 that the blackboard system stores information that is shared between the proposed process models in building a forward prediction of future pan stage operating conditions over a forecast horizon.

5.4.3.3 Integration Summary of Process Models with Fuzzy If-Then Rules

A summary of the integration procedures, for the merger of the pan stage process models with fuzzy If-Then rules used for localisation adaption to match real world operating conditions, that have been covered in this section now follows.

The dotted lines in Figure 34 indicate optional processes that may be performed. The pre-processing and post-processing phases are only undertaken on the provision that fuzzy If-Then rules have been defined for the particular pan stage process model under consideration. This approach promotes independent development of pan stage process models and linkage with rules.

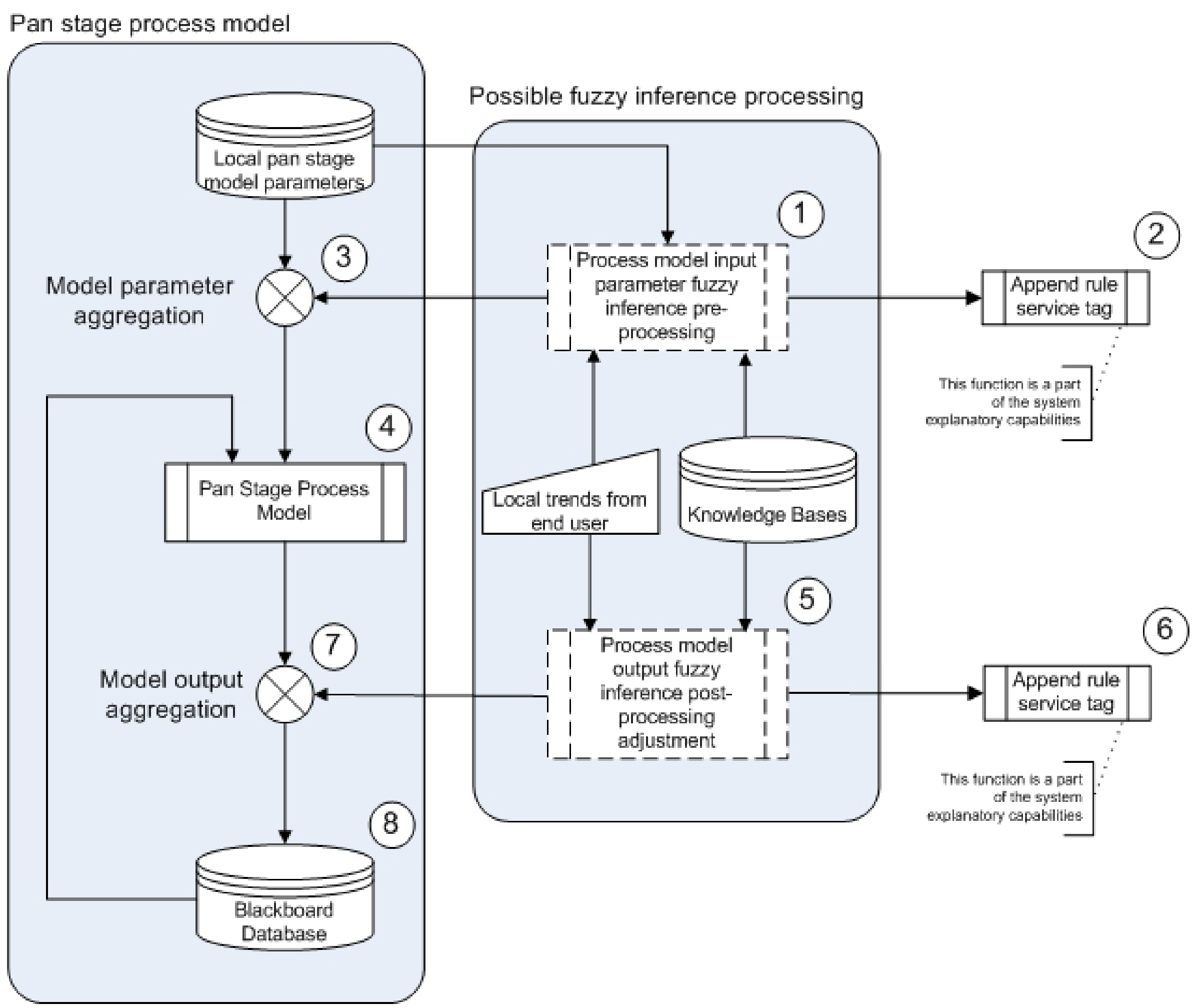

Figure 34: Annotated pan stage process model interaction diagram with fuzzy inference pre-processing and post-processing functionality of process model input and output data

Annotated numbers within the figure refer directly to the order of processing steps for the fuzzy inference pre-processing and post-processing localisation adjustments working in tandem with the pan stage process models and the KBSSS explanatory subsystem.

These steps are:

1. Fuzzy pre-processing localisation of pan stage process model input parameters is performed to match with real world operating conditions.

2. Rule service tags for firing If-Then fuzzy rules are appended to the active tracking table to assist in the justification and explanation process. This process is detailed in Section 5.5 and works to assist in providing explanation and justification capabilities of the system results and how they were achieved.

3. Defuzzification is used to provide crisp data from results of the fuzzy inference pre-processing phase. Aggregation of these results with the default process model parameters then occurs with higher precedence given to the use of the results of the pre-processing phase.

4. The current pan stage process model to be evaluated is run. An individual model assists in the process of building an overall forward forecast of pan stage operating conditions.

5. Fuzzy post-processing localisation of pan stage process model output results is performed to match with real world operating conditions.

6. This step functions in the same manner as step 2.

7. Defuzzification is used to provide crisp data from results of the fuzzy inference post-processing phase. Aggregation of these results with the process model output results then occurs with higher precedence given to the use of the results of the post-processing phase.

8. Final pan stage process model results are saved to blackboard data repository for use by other process models in building the forecast of future pan stage operating conditions.

This iterative process is undertaken until all of the pan stage process models have been run in line with the scheduling directives of the blackboard system scheduler component and in meeting with the data dependencies that exist between the process models as presented in Figure 28.

5.4.4 Prediction Methodology for Integrated Pan Stage Process Models with Fuzzy Rule Base

The following section details the methodology used in the merger of the dynamic pan stage process models and the fuzzy rule base. Program statement blocks are used to show the sub-tasks undertaken in the prediction process. Scheduling of the procedures called within the main forecast block is undertaken by the blackboard scheduling system and maintains the data integrity and order presented in Figure 28. One possible sequence of calling subsystem pan stage process models in order to carry out the forward prediction has been presented. This sequence of operations builds the forward prediction of pan stage operating conditions and works in tandem with the fuzzy rule integration methodology presented in Section 5.4.3.

begin **procedure_forecast**

call **procedure_P_1** *//Syrup rate prediction model*

call **procedure_P_2** *//Pan stage steady state flow model*

call **procedure_P_3** *//Empirical vacuum pan models*

call **procedure_P_4** *//Vacuum pan phase determination and forecast models*

call **procedure_P_5** *//Stock tank prediction models*

call **procedure_P_6** *//Schedule optimisation*

end **function_forecast**

begin **procedure_P_1** *//Syrup rate prediction model*

infer input parameters against knowledge base *//Fuzzy inference pre-processing*

aggregate input and call **procedure_syrup_rate_prediction_model**

infer output *//Fuzzy inference post-processing*

aggregate output and save results to blackboard

end **procedure_P_1**

begin **procedure_P$_2$** *//Pan stage steady state flow model*

infer input parameters against knowledge base *//Fuzzy inference pre-processing*

aggregate input and call **procedure_pan_stage_steady_state_flow_model**

infer output *//Fuzzy inference post-processing*

aggregate output and save results to blackboard

end **procedure_P$_2$**

begin **procedure_P$_3$** *//Empirical vacuum pan models*

infer output *//Fuzzy inference post-processing of static models*

aggregate output and save results to blackboard

end **procedure_P$_3$**

begin **procedure_P$_4$** *//Vacuum pan phase determination and forecast models*

infer input parameters against knowledge base *//Fuzzy inference pre-processing*

aggregate input and call **procedure_vacuum_pan_phase_determination_and_forecast_models**

infer output *//Fuzzy inference post-processing*

aggregate output and save results to blackboard

end **procedure_P$_4$**

begin **procedure_P$_5$** *//Stock tank prediction models*

infer input parameters against knowledge base *//Fuzzy inference pre-processing*

aggregate input and call **procedure_stock_tank_prediction_models**

infer output *//Fuzzy inference post-processing*

aggregate output and save results to blackboard

end **procedure_P$_5$**

begin **procedure_P$_6$** *//Schedule optimisation*

infer input parameters against knowledge base *//Fuzzy inference pre-processing*

aggregate input and call **procedure_schedule_optimisation**

infer output *//Fuzzy inference post-processing* aggregate output and save results to blackboard

end **procedure_P_6**

5.5 Explanatory Capabilities (Discourse Semantics)

In order for the KBSSS to provide explanatory capabilities, a slimline version of the Rule Explanation for Expert Systems Using Service Tags, Tables and Tracing (REST3) method developed in previous research (Chiou and Yu, 2007a) has been adapted and implemented. Each fuzzy If-Then rule in the KBSSS has an information tag component that acts as a reference to stored explanatory information. This information assists in justifying the rationale behind the fuzzy rules. For each rule fired as part of the inference process, the explanatory subsystem builds a table of active rules and then works collectively with the discourse/explanatory knowledge base to provide supporting information.

This generation of supporting justifications does not interact in any way with the pan stage process models or fuzzy inference process that takes place. This mechanism is kept separate in order to act as an independent and impartial subsystem. In line with the KBSSS requirements simple English based sentences are used to provide explanatory support on system recommendations and advice. The system explanations are stored in database format as part of the discourse/explanatory knowledge base presented in Figure 8. At the end of the process the supporting explanations are integrated and formatted for presentation to support the final KBSSS justifications and recommendations.

When fuzzy rules fire as part of the inference process the service tag appended to the rule along with the degree of fulfilment value from the rule predicate and the rule number are transferred and stored as an entry in the *Active Table*. The tuple representing a row in the Active Table is:

{ServiceTag, RuleNumber, DegreeOfFulfilment, ModelName}

where,

ServiceTag *is an integer value representing a unique identifier for reference with the discourse/explanation knowledgebase,*

RuleNumber *is a unique integer identifier of the firing fuzzy rule,*

DegreeOfFulfilment *is the degree of fulfilment from the fuzzy rule predicate,*

ModelName *is a character string sequence identifying the pan stage process model that the fuzzy rule is identified with.*

This system provides a linear rule trace for active rules that are firing due to the inference process. If the degree of fulfilment exceeds the threshold, which is defined as part of the fuzzy rule parameters, then an active database lookup is performed to retrieve the explanation for the associated ServiceTag from the *Discourse/Explanation Knowledge Base*. The tuple representing a row in the Discourse/Explanation Knowledge Base is:

{ServiceTag, Explanation}

where,

ServiceTag *is an integer value and unique identifier for explanations stored within the discourse/explanation knowledgebase,*

Explanation *is a sequence of characters forming the rule supporting explanation in English.*

The ServiceTag and Explanation information are appended to a *Discourse Proforma Table* as active explanations along with the associated name of the process model associated with the firing fuzzy rule. This modification is unique to the KBSSS implementation and associates explanations and supporting advice with the individual process model associated with the active fuzzy rules to assist in final formatting. The tuple representing a row in the Discourse Proforma table is:

{ServiceTag, Explanation, ModelName, ProcessingType}

where,

ServiceTag *is an integer value and unique identifier for explanations stored within the discourse/explanation knowledgebase,*

Explanation *is a sequence of characters forming the discourse explanation in English,*

ModelName *is a character string sequence identifying the pan stage process model that the fuzzy rule is identified with,*

ProcessingType *is integer identifying whether the discourse explanation is associated with fuzzy rule pre-processing or post-processing localisation.*

The program structure for the explanatory subsystem is presented in Figure 35. The subsystem is scheduled by the blackboard system scheduler, as outlined in Section 5.3.2, after the forward forecast by the pan stage process models working in tandem with the fuzzy inference process has been undertaken.

Service tags resulting from the inference process form the primary input for this major subsystem. These tags are collated for further processing by the described REST3 process.

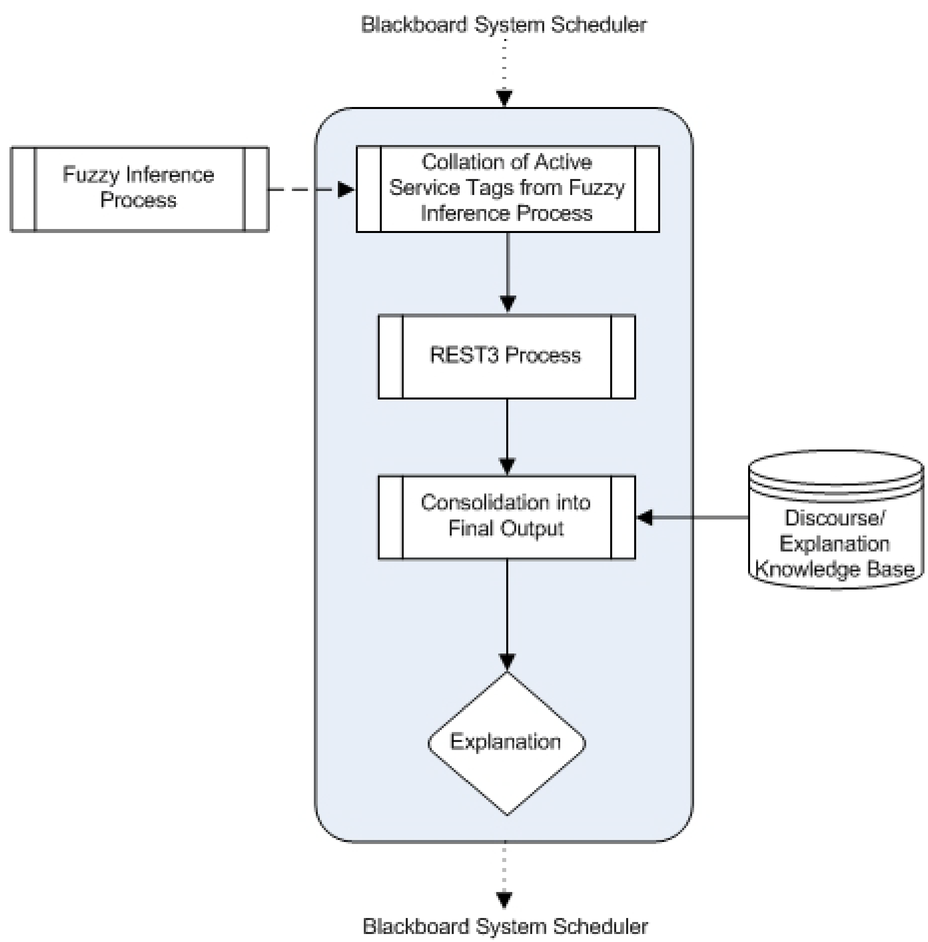

Figure 35: Program structure for discourse semantics in providing explanatory capabilities adapted from previous research (Chiou and Yu, 2007a)

As part of this process they are cross referenced with explanation information stored in the discourse/explanatory knowledge base and consolidated as part of the discourse proforma before final formatting. This proforma information is formatted to display the final systems explanations and justifications to provide support for the primary KBSSS advice and recommendations.

5.6 Summary

This chapter has covered in detail the design and implementation of the three core intelligent system supporting technologies. The first subsystem reviewed within this chapter provides a prediction of pan stage operating conditions. A series of dynamic industrial pan stage process models were proposed to describe the interactions of the pan stage with the syrup production and centrifugal sections along with stock tank models, using vacuum pan phase determination and empirical vacuum pan models, to forecast stock tank levels. A schedule optimisation model based upon an adapted pan stage steady state flow model approach was also developed, encompassing the proposed models, in order to affect efficient scheduling of vacuum pans on the stage while minimising steam usage, boosting productivity and maintaining adequate stock material levels.

These models were aiding by two core supporting technologies developed specifically for model functionality. A time based methodology was employed for mapping forecast production quantities and apportioning them to future time intervals. It provided a unifying system for pan stage process model forecasting though the allocation of prediction quantities to future forecast intervals. This technique is a fundamental and core component of the KBSSS that acts cooperatively with the process models to provide forecast capabilities. A blackboard system for information exchange between major subsystems and dynamic industrial process models was also developed. A blackboard scheduling system was also proposed due to the hierarchical nature of the proposed pan stage process models and their interaction with the fuzzy inference engine for localisation adaption.

An integration method for merger of the dynamic industrial pan stage process models was proposed as part of the second core KBSSS subsystem. This method utilised fuzzy logic pre-processing and post-processing adjustment applied to pan stage process model input parameters and output results respectively for the proposed process models. This incorporation of the dynamic process models as part of the fuzzy If-Then rule consequent components allowed features particular to each model to be isolated for localisation adaption to account for local trends through the influence of dynamic real world data only known at system runtime.

The final subsystem described in this chapter is the explanatory capabilities. A fuzzy rule based system using tags and tables has been adapted from previous research for use within the KBSSS. This mechanism allows the KBSSS to provide explanation and justification support to garner user acceptance of primary system recommendations.

In the following chapter the functionality of the KBSSS will be demonstrated in two ways. The first will demonstrate how expert knowledge is transformed into a fuzzy If-Then rule using the proposed industrial process models working in tandem with the fuzzy inference system and explanatory capabilities. The second phase will demonstrate the KBSSS's capabilities in the provision of strategies for management and best practices. Predictions of future pan stage operating conditions will be compared and evaluated against pan stage control system information to assist in validation of the proposed pan stage process models working in conjunction with the fuzzy inference engine.

Chapter 6: Modelling, Testing and Results

6.1 Introduction

This chapter will demonstrate the functionality and capabilities of the developed KBSSS software application. This will include the process on how fuzzy If-Then rules are developed and implemented as part of expert knowledge and testing of the results provided by the KBSSS. These results will be tested against control system data for their evaluation. A discussion of the test results will be undertaken after each stage of the test is performed.

This chapter is structured as follows. Section 6.2 details the operational levels within the KBSSS and the system interaction with different users. Section 6.3 details the knowledge acquisition process in building and storing expert knowledge as part of the KBSSS knowledge and discourse bases. Section 6.4 outlines the process of system consultation with Section 6.5 presenting and discussing KBSSS test results.

6.2 Process Flow and Operation Levels

The KBSSS is supported by the seven databases detailed in Figure 8 of Chapter 4. During KBSSS operation, the access and modification of data within these information sources occurs at two levels of operation. These levels are:

1. Knowledge acquisition process, and

2. Consultation process.

Through the knowledge acquisition process knowledge engineers, content experts and pan stage experts model pan stage knowledge with the information extracted from thisprocess stored as part of the KBSSS data sources. The consultation process level allows end users to interact with the KBSSS for advice, recommendations and supporting information in the provision of best practices and management for pan stage operations.

Systems users fall into four distinct categories. End users interact in a consulting fashion with the KBSSS in the provision of its advice. Knowledge engineers and content experts develop and maintain the system knowledge and discourse bases used in modelling expert knowledge and explanatory capabilities. Pan stage experts develop and maintain the dynamic industrial pan stage process models and their default model parameters used in the prediction of future operating conditions. The final system group is a *pseudo-user* interaction maintained by the sugar mill control system data sources. Information sources from cane receival, juice processing station, pan stage and centrifugal station are real world information sources that the KBSSS draws from during its operation.

The seven database systems used in the KBSSS are grouped depending upon functionality. This clustering is:

1. **Real world databases** consisting of user dynamic data and sugar mill dynamic data;
2. **System supporting database** consisting of blackboard database;
3. **Knowledge bases** consisting of the KBSSS knowledge base and fuzzy If-Then rule base;
4. **Discourse base** comprising the discourse/explanation knowledge base; and
5. **Model parameter database** comprised of databases storing default pan stage process model parameters.

These functional groups are annotated with the same clustering levels in Figure 36 which shows interaction with the detailed KBSSS user groups as part of the consultation and knowledge acquisition phases of operation. Reference to this diagram is made in the proceeding subsections in the explanation of the knowledge acquisition and consultation processes.

6.2.1 Knowledge Acquisition Level

The knowledge acquisition process is outlined in Figure 36. The users at this level are the content experts, knowledge engineers and pan stage experts.

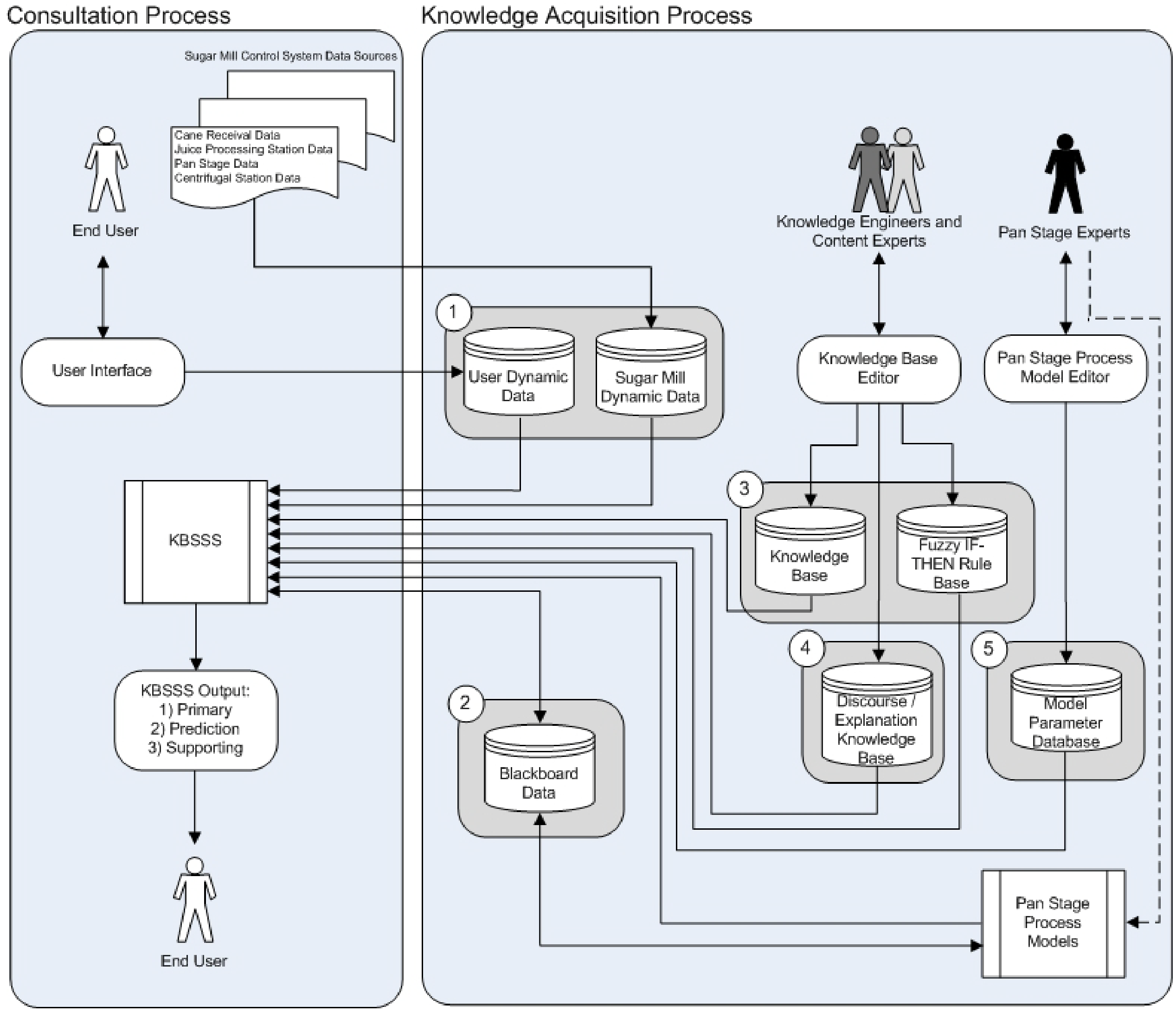

Figure 36: KBSSS process flow showing interaction of the major user groups with the major information sources for the knowledge acquisition and consultation processes

The knowledge bases are developed by the knowledge engineers to establish relationships in best practices and management of the pan stage. Knowledge is translated into fuzzy membership functions as part of the process of building fuzzy If-Then rules to model pan stage relationships. This transformation occurs through the use of the knowledge base editor. Content engineers then establish the discourse relationships between the fuzzy rules and explanations.

The dynamic industrial pan stage process models are initially developed by pan stage experts and hardcoded into the KBSSS software application. This relationship is indicated by the broken line in Figure 36 since the implemented pan stage process models are not able to be directly changed and exist as software. These models directly form part of the hard coded system knowledge detailing the pan stage process and dynamic interrelations between segments in complex factory environment, as detailed in Section 5.2. The pan stage experts also develop the industrial process model default parameters that are used as part of the pan stage process models. These parameters are transformed through the pan stage process model editor and saved to the appropriate model databases. These defaults are overridden by the fuzzy If-Then rules to provide adaption to account for real world operating conditions and local trends.

Information sources from the real world databases are fundamentally different in comparison to the static knowledge bases. Whereas the knowledge bases are essentially static over the lifetime of the KBSSS, given allowance for maintenance procedures, the real world databases provide information sources that are dynamic and vary with time. Dynamic user data is elicited in consultation with the end user in providing system advice and recommendations. Information provided by end users has a much greater lifespan than control system information which is essentially a constant information stream. Information sources from the sugar mill controls system provides real time information on cane receival, juice processing, pan stage and centrifugal sections of the sugar mill through a parasitic data link to existing sugar mill infrastructure. Given the changing nature of these information sources, updated information from these sources is required each time the KBSSS carries out its processing regime in the generation of advice, recommendations, supporting explanations and a future forecast of pan stage operating conditions.

An additional key information source is the system supporting database composed of the blackboard system. This information storage repository stores partial solutions in building the forward forecast of pan stage operations as presented in section 5.2.3 with information flows controlled by the blackboard scheduling system.

6.2.2 Consultation Process Level

The consultation process as shown in Figure 36 involves interaction between the end user, sugar mill control system data sources and the KBSSS. The end user supplies information real world information on current operating conditions and trends. This information along with data provided by the sugar mill control system is captured and stored for use in both the inference process and by the dynamic industrial pan stage process models. As detailed in the previous section, updated information is required each time the KBSSS carries out its processing regime.

User supplied information from the consultation process, along with pan stage control system data is used in the inference process and prediction of future pan stage operating conditions by the industrial pan stage process models. These two major subsystems and their cooperative interactions were specified in Chapter 5. The results of this process are the primary systems recommendations with supporting outputs as detailed in Section 4.2. The consultation process ends with the generation of the final system outputs. Based upon the system recommendations and reasoning presented, the end user will determine which operational decisions should be made using the pan stage forecast of future operating conditions as supporting information in the decision making process.

6.3 An Example of the Knowledge Acquisition Process

This section will demonstrate the procedure, through example, of extracting fuzzy If-Then rules from expert knowledge and outline the construction of the underlying KBSSS knowledge bases used in the storage of rule information. These modelled rules will later be used in the test case presented in this chapter. As part of this example the storage mechanisms for the implementation of service tags for explanatory capabilities will also be covered. An example of model parameters and associated database storage for the pan stage process model, that is associated with the developed fuzzy If-Then rule, will also be detailed.

Given that the knowledge bases of the KBSSS are static in nature, the knowledge acquisition process and development of fuzzy rules need only occur once during the KBSSS lifecycle. Periodic adjustments to factory infrastructure, factory upgrades and changes to factory operational procedures may however necessitate some maintenance and fine-tuning of both the fuzzy If-Then rules and default process model parameters throughout the lifespan of the KBSSS. These maintenance procedures are beyond the scope of the thesis.

6.3.1 Process Model Default Parameters and Database Structure

The pan stage process models are specialised components forming part of the overall system knowledge base. The default model parameters for the pan stage steady state flow model, for which a fuzzy If-Then rule is developed in subsequent sections, follow. These customizable model parameters are typical of mid seasonal sugar factory conditions for the production of Brand 1 grade sugar (Broadfoot and Pennisi, 2001). The defined parameters pertain to the process model detailed in Section 5.2.2. The customisable parameter sets, with their initial settings, for this model are:

Sugar Purity {A, B, C} = {99.326, 98.898, 88.0} %

Fugal Molasses Purity Rise {A, B, C} = {1.481, 2.286, 1.723} %

Target Purities {A Massecuite, B Massecuite, C Graining, Final Molasses} = {88.59, 82.0, 70.0, 48.4} %

Target Sugar Crystal Length {A Sugar, B Sugar, C Sugar, Product} = {0.9, 0.85, 0.28, 0.88} mm

Coefficient of Variation of Sugar Crystal Length {A Sugar, B Sugar, C Sugar, Product} = {0.27, 0.35, 0.35, 0.35}

B Sugar Fractions {A Seed, Product, Remelt} = {0.0, 1.0, 0.0}

Graining Fraction {C Pan} = {0.22}

C Sugar Fractions {A Seed, B Seed, Remelt} = {0.11, 0.08, 0.81}

Liquor Tank Fractions {A Seed, B Seed} = {0.5, 0.5}

A Molasses Tank Fractions {A Seed, B Seed, C Seed, Final Molasses} = {0.45, 0.45, 0.1, 0.0}

B Molasses Tank Fractions {B Seed, C Seed, Final Molasses} = {0.0, 1.0, 0.0}

Crystal Content on Solids {A Pan, B Pan, C Pan, C Sugar Screw} = {57.6, 51.9, 32.0, 35.0} %

Dry Substance Values {A Massecuite, B Massecuite, C Massecuite, Syrup, Remelt, A Molasses, B Molasses, C Molasses} = {90.66, 91.48, 92.01, 68.0, 67.0, 69.0, 69.0, 77.0} %

Maximum Iterations for Optimisation Loops {Mass Balance, Purity Balance} = {30, 1000}

Tolerance Values {Mass Balance Convergence, Purity Target Convergence, Sugar Size} = {0.01 t/h, 0.01 %, 0.001 mm}

A Sugar Purity	99.326
B Sugar Purity	98.898
C Sugar Purity	88.000
A Fugal Molasses Purity Rise	1.481
B Fugal Molasses Purity Rise	2.286
C Fugal Molasses Purity Rise	1.723
A Massecuite Target Purity	88.59
B Massecuite Target Purity	82.00
C Graining Target Purity	80.00
Final Molasses Target Purity	48.40
A Sugar Target Sugar Crystal Length	0.90
B Sugar Target Sugar Crystal Length	0.85
C Sugar Target Sugar Crystal Length	0.28
Product Sugar Target Sugar Crystal Length	0.88
A Sugar Coefficient of Variation of Sugar Crystal Length	0.27
B Sugar Coefficient of Variation of Sugar Crystal Length	0.35
C Sugar Coefficient of Variation of Sugar Crystal Length	0.35
Product Sugar Coefficient of Variation of Sugar Crystal Length	0.35
B Sugar Fraction To A Seed	0.00
B Sugar Fraction To Product Sugar	1.00
B Sugar Fraction To Remelt	0.00
C Pan Graining Fraction	0.22
C Sugar Fraction To A Seed	0.11
C Sugar Fraction To B Seed	0.08
C Sugar Fraction To Remelt	0.81
Liquor Tank Fraction To A Seed	0.50
Liquor Tank Fraction To B Seed	0.50
A Molasses Tank Fraction To A Seed	0.45
A Molasses Tank Fraction To B Seed	0.45
A Molasses Tank Fraction To C Seed	0.10
A Molasses Tank Fraction To Final Molasses	0.00
B Molasses Tank Fraction To B Seed	0.00
B Molasses Tank Fraction To C Seed	1.00
B Molasses Tank Fraction To Final Molasses	0.00
A Pan Crystal Content on Solids	57.60
B Pan Crystal Content on Solids	51.90
C Pan Crystal Content on Solids	32.00
C Sugar Screw Crystal Content on Solids	35.00
A Massecuite Dry Substance Value	90.66
B Massecuite Dry Substance Value	91.48
C Massecuite Dry Substance Value	92.01
Syrup Dry Substance Value	68.00
Remelt Dry Substance Value	67.0
A Molasses Dry Substance Value	69.0
B Molasses Dry Substance Value	69.0
C Molasses Dry Substance Value	77.0
Mass Balance Maximum Iterations for Optimisation Loops	30
Purity Balance Maximum Iterations for Optimisation Loops	1000
Mass Balance Convergence Tolerance Value	0.010
Purity Target Convergence Tolerance Value	0.010
Sugar Size Tolerance Value	0.001

Table 5: Pan stage steady state flow model database parameters

These parameters are transformed into the database entry, shown in Table 5, with process model parameters forming the table column names and parameters forming the tuple entry.

Model parameters are stored as specialised databases constructed under an industry standard RDBMS database server. Separate databases are used to store information particular to each of the process models. Use of an industry standard RDBMS database server ensures system interoperability and ease of consultation for data access.

Default model parameters for each of the pan stage process models can be adjusted through the use of the pan stage model parameter editor. An editor interface through the KBSSS allows for adjustment of the major model default parameters. These parameters are loaded and used in the absence of fuzzy rules providing pre-processing localisation adjustments which accounts for real world operating conditions.

Each of these default parameters controls functionality of the pan stage steady state flow model. The initial model parameter settings and adjustment through the KBSSS maintenance phase of software lifecycle are undertaken by experts with knowledge specific to pan stage operations. These experts have an understanding of the functionality and rationale of the process model characteristics, performance and operational mechanics and how these factors are influenced by the default process model parameters.

Similarly, default model parameters exist for all of the pan stage process models with these default parameters able to be customized to suit a generic implementation of the process model. The following sections detail the procedures for creation of Fuzzy If-Then rules which allows localisation of input model parameters to account for real world data that is not part of the predefined static knowledge base and allows for a mechanism to override of the default model parameters. This approach was previously presented in Section 5.4.3.

6.3.2 Fuzzy Modelling and [Basic] If-Then Rule Extraction

This section details how one of the rules from the KBSSS's knowledge and rule base is modelled and subsequently transformed into a fuzzy If-Then rule. By way of this process a statement such as "If it is early season then the A fugal purity rise is 1.635 units" which is inferred from prior research (Broadfoot and Pennisi, 2001) can be transformed into a fuzzy representation and then developed into a fuzzy If-Then rule by knowledge engineers. In the modelling process the fuzzy variables and predicates are defined as part of the first step.

Syrup quantity and purity is the greatest contributing factor to results from the pan stage as this is the primary inputs to this section of the sugar factory. With the end of cane crushing season it is normally assumed that conditions are reasonably similar to early season cane in general. Compared to the mid-season period, the CCS levels of cane and consequently syrup purity to the pan stage falls with the concentration of soluble impurities rising. The syrup purity falls to comparable levels to those existing at early season (Broadfoot and Pennisi, 2001). This effect creates a see-saw like effect where conditions at early season are similar to those existing at the end of season but differ during the mid-season cane crushing period.

Typically the cane crushing season last for between 20-25 weeks of the year. This forms the basis for the universe of discourse for the fuzzy season set. The early season is typically of the first four or so weeks of the season with the mid season period lasting for 6 or more weeks (Broadfoot and Pennisi, 2001). Since the late season has conditions typical of early season the same period can be assumed. From this information the fuzzy antecendent linguistic variable *season* can be inferred along with the predicates *early*, *mid* and *late*.

The fugal purity rise is the difference between the purity of molasses from the fugals and the purity of the mother syrup surrounding the sugar crystals in the massecuite. This increase in the purity of molasses during the fugalling process can be attributed to the following conditions when fugalling the massecuite (Sugar Research Institute, 2004):

- for batch centrifugalling the basket wash dissolves some of the sugar;
- some sugar crystal passes through the fugal gauze; and
- some sugar crystal is dissolved by the fugal spray wash.

This results in a purity rise typically in the range of one to four units. Figure 37 provides a simplified version of the process material streams resulting from the centrifugal actions.

In this example the fugal purity rise has a defined fixed value. The defined fugal purity rise value is defined through the use of a fuzzy singleton. These fuzzy functions have a degree of fulfilment value of 1 for a single universe of discourse value and are 0 elsewhere. For the

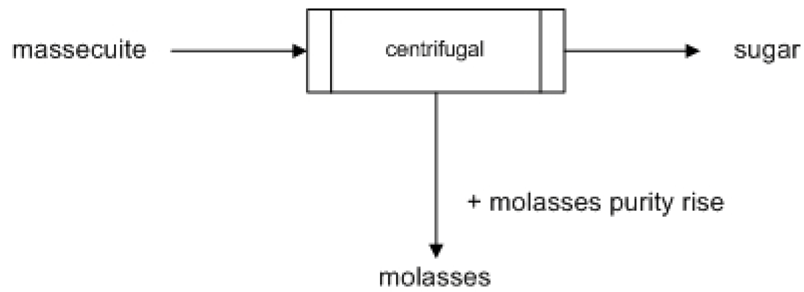

Figure 37: Centrifugal material stream interaction denoting the molasses purity rise

statement to be modelled we can now infer that the consequent linguistic variable *A fugal purity rise* has an associated predicate value of 1.635 units. In conjunction with prior research (Broadfoot and Pennisi, 2001) it can also be determined that the mid season A fugal purity rise is 1.481 units. The consequent linguistic variable now has the predicate values of *"1.635"* and *"1.481"* units. Accounting for the previously discussed seasonal influences on pan stage processing, the fuzzy membership functions for the antecedent and consequents are as indicated in Figure 38.

The corresponding If-Then fuzzy set of rules is:

If season is *early* **Then** steady_state_flow_model:AFugalPurityRise = 1.635

If season is *mid* **Then** steady_state_flow_model:AFugalPurityRise = 1.481

If season is *late* **Then** steady_state_flow_model:AFugalPurityRise = 1.635

This is an example of modelling of a fuzzy If-Then rule represented in Equation (5.9) of the previous chapter. The A fugal purity rise value of the rule consequent rule is attached to the steady state flow model, from Section 5.2.2, as one of the process model input parameters.

After completion of the modelling process, the fuzzy data can be converted for system use through *fuzzy variable editing* through the KBSSS input layer. This process facilitates the declaration of the fuzzy variables. The fuzzy variable is allocated a name along with minimum and maximum values for the defined universe of discourse. A resolution is specified for the incremental step allowed when allocating membership functions within the universe of discourse. The type of variable is declared either being allocated as a rule antecedent (specified as type 1) or consequent (specified as type 2) variable. This information determines the relational linkage between the data source and data source variable name in being linked to the fuzzy variable. Each declared fuzzy variable is identified with a unique identifying number allocated automatically by the RDBMS upon creation of the data base record for the fuzzy variable.

Each fuzzy predicate within the fuzzy set is also sequentially allocated a predicate ID number to uniquely identify them. A predicate name along with membership function type is stored for each of the fuzzy predicates. Each of the predicates is allocated a membership function and based upon the type of shape the associated membership function type is stored. A parameter value of 1 indicates a *left-shouldered triangle*, 2 is a *standard triangle*, 3 is a *right-shouldered triangle*, and 4 is a *singleton*. Additionally, the provision for custom membership functions is also allowed. For each fuzzy membership function, representing the fuzzy predicate, a list of parameters is required. The number of parameters is allocated sequentially and dependant upon the fuzzy membership function selected. The triangle based fuzzy membership functions require the storage of all store three parameters and fuzzy singletons have data requirements for a single parameter. Each parameter is allocated sequentially and has a unique identifying ID. This is stored with the fuzzy variable ID and predicate ID as part of the relational database storage mechanics to allow for compact data storage and ease of information lookup.

After declaration of the fuzzy variables and predicates, the next step in the process is the declaration of the fuzzy If-Then rules. Each of the three fuzzy If-Then rules declared in the

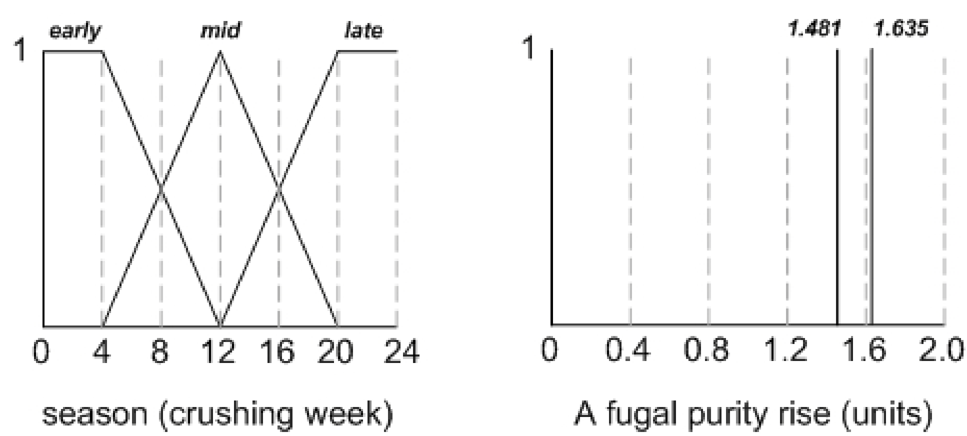

Figure 38: The membership for the antecedent rule component is the point in season and the consequent rule component is the A fugal purity rise

rule block previously are allocated sequentially. Due to the relational database format only previously defined fuzzy predicates with their associated fuzzy variables are able to be allocated at this step.

For each fuzzy If-Then rule, the fuzzy set ID and fuzzy predicate ID entering into the relationship on both the antecedent and consequent sides of the rule are required. This is stored against a unique rule ID which identifies the fuzzy If-Then rule being added to the KBSSS fuzzy rule base. Additional antecedent and consequent components of the fuzzy rule may be linked through compound fuzzy AND (fuzzy intersection) or OR (fuzzy union) operators in order to conform with standard fuzzy compound based rules. Additionally, the process model that the fuzzy rule is associated with is stored as well as the processing type. This may either be a rule for pre-processing as indicated by a *1* value or a post-processing rule as indicated by a value of *2*. This determines whether the rule is evaluated before or after the defined process model as part of fuzzy localisation for real world data. For each of the defined fuzzy rules, service tags for discourse explanations are also stored. This is discussed next in Section 6.3.3.

After completion of these defined steps in the fuzzy variable, predicate and rule creation process, the KBSSS makes appropriate changes to the knowledge and rule bases and inserts the appropriate data entries into the system tables. The database table entries for the knowledge base and If-Then rules are presented in Section 6.3.4.

6.3.3 Implementing Explanatory Service Tags

The KBSSS provides facilities for editing the discourse/explanatory knowledge base through the knowledge base/content expert editing interface with interactions depicted in Figure 8. These facilities allow the attachment of rule explanations to each of the fuzzy If-Then rules with this information then stored in the system databases. In keeping within KBSSS requirements, explanations formed in plain English sentences are used to provide explanatory support on system recommendations and advice. The KBSSS specifications do not require complex supporting information so this format is acceptable for end user advice. The following service tag identifies the mid-season discourse entry associated with the fuzzy If-Then rule developed in the preceding section. The database table entries are presented in Section 6.3.4.

Service Tag Number: 7

"The fugal purity rise varies with the point in the cane crushing season. Compared to the mid-season, the fugal purity rise is higher during the early and late season. The current point in the crushing season is mid."

Associated with a specific fuzzy If-Then rules/s the service tag numbers are unique and allocated sequentially by the RDBMS when the insertion of new rules to the discourse/explanatory base occurs. This unique numbering allows identification and access to specific discourse explanations.

The discourse explanations are linked with the fuzzy If-Then rules through the service tag number and the fuzzy If-Then rule number which are unique identifiers in establishing the data relationship. Also entering into this relationship is the degree of fulfilment threshold for the fuzzy rule that the discourse explanation is developed for. For service tag number 7 a value of 0.5 allows explanatory discourse activation when the rule degree of fulfilment exceeds this value.

Tagged explanations to rules are also associated with pan stage process models. This helps in determining appropriate formatting for presentation to end users. The use of degree of fulfilment thresholds, used in determining when the rule is active within the explanatory process, was previously outlined in Section 5.5.

6.3.4 Knowledge Rule Base and Discourse Base Structure

As a result of the data acquisition process the following tables will be constructed as part of the knowledge base, fuzzy If-Then rule base and discourse/explanation bases. The previously defined fuzzy variables, fuzzy predicates, membership functions, fuzzy If-Then rules and discourse for explanations will be inserted as table data within Table 6, Table 7, Table 8, Table 9, Table 10 and Table 11.

Fuzzy variables:

FuzzyVarID	FuzzyVariableName	MinValue	MaxValue	Resolution	Type	Datasource	VariableName
7	Season	0	24	1	1	UserInput	season
8	AFugalPurityRise	0	2	0.001	2	SteadyStateFlowModel	AFugalPurityRise

Table 6: Table data for fuzzy set declarations

Fuzzy predicates:

FuzzyVarID	PredicateID	PredicateName	MFType
7	1	early	1
7	2	mid	2
7	3	late	3
8	1	1.481	4
8	2	1.635	4

Table 7: Table data for fuzzy predicate declarations

Consequent dynamic linkage to either singletons or data sources:

FuzzyVarID	LinkageType
8	1

Table 8: Table data for consequent dynamic linkage

Fuzzy membership function parameters:

FuzzyVarID	PredicateID	ParameterID	Value
7	1	1	0
7	1	2	4
7	1	3	12
7	2	1	4
7	2	2	12
7	2	3	20
7	3	1	12
7	3	2	20
7	3	3	24
8	1	1	1.481
8	2	1	1.635

Table 9: Table data for fuzzy membership function parameter declarations

Fuzzy If-Then Rules:

RuleID	ServiceTagID	LHSSetID	LHSPredID	RHSSetID	RHSPredID	Type	ProcessModelName	DOFThreshold
19	6	7	1	8	2	1	SteadyStateFlowModel	0.5
20	7	7	2	8	1	1	SteadyStateFlowModel	0.5
21	8	7	3	8	2	1	SteadyStateFlowModel	0.5

Table 10: Table data for fuzzy If-Then rule and explanatory declarations

Discourse explanations:

ServiceTagID	Explanation
6	The fugal purity rise varies with the point in the cane crushing season. Compared to the mid-season, the fugal purity rise is higher during the early and late season. The current point in the crushing season is early.
7	The fugal purity rise varies with the point in the cane crushing season. Compared to the mid-season, the fugal purity rise is higher during the early and late season. The current point in the crushing season is mid.
8	The fugal purity rise varies with the point in the cane crushing season. Compared to the mid-season, the fugal purity rise is higher during the early and late season. The current point in the season is late.

Table 11: Table data for discourse declarations

These databases utilise the relational database storage methodology for compact representation and adhere to database normalisation standards (Kroenke, 1997). This database structuring allows for ease of use and efficient information storage, retrieval and modification with no data anomalies.

6.3.5 Summary of the Knowledge Acquisition Phase Process Flow

The knowledge acquisition process can be summarised by Figure 39. The knowledge acquisition process starts with the modelling and development process of the pan stage process models and derivation of the key default parameters which allows a generic implementation of the pan stage process models.

After establishing the fuzzy sets, predicates and membership functions, fuzzy If-Then rules are then developed by relating antecedent and consequent predicates from the fuzzy sets together. Fuzzy sets may then be linked to the pan stage process models, with the fuzzy If-Then rules providing capabilities for pre-processing and post-processing localisation adjustments to the pan stage process model input parameters and output data.

Explanations are then tagged to each of the fuzzy rules, to allow for the use of discourse advice, along with threshold level required for their activation. The final results of this process are database records stored at the knowledge base, fuzzy If-Then rule base and discourse/explanatory base level.

6.4 Consultation Process

The second portion of this chapter examines simulation results from the KBSSS. These results will be compared against pan stage control system data provided by Racecourse sugar mill (located in Mackay, Queensland).

A sample test case will be detailed in the following sections focusing on the following system outputs:

1. prediction of pan stage operating conditions; and
2. final advice to end users.

The user input provided from the consultation process is combined with the fuzzy inference process along with control system data required for pan stage process model, described in Section 5.2, and their default parameters. Collectively this combination of data forms the KBSSS system inputs.

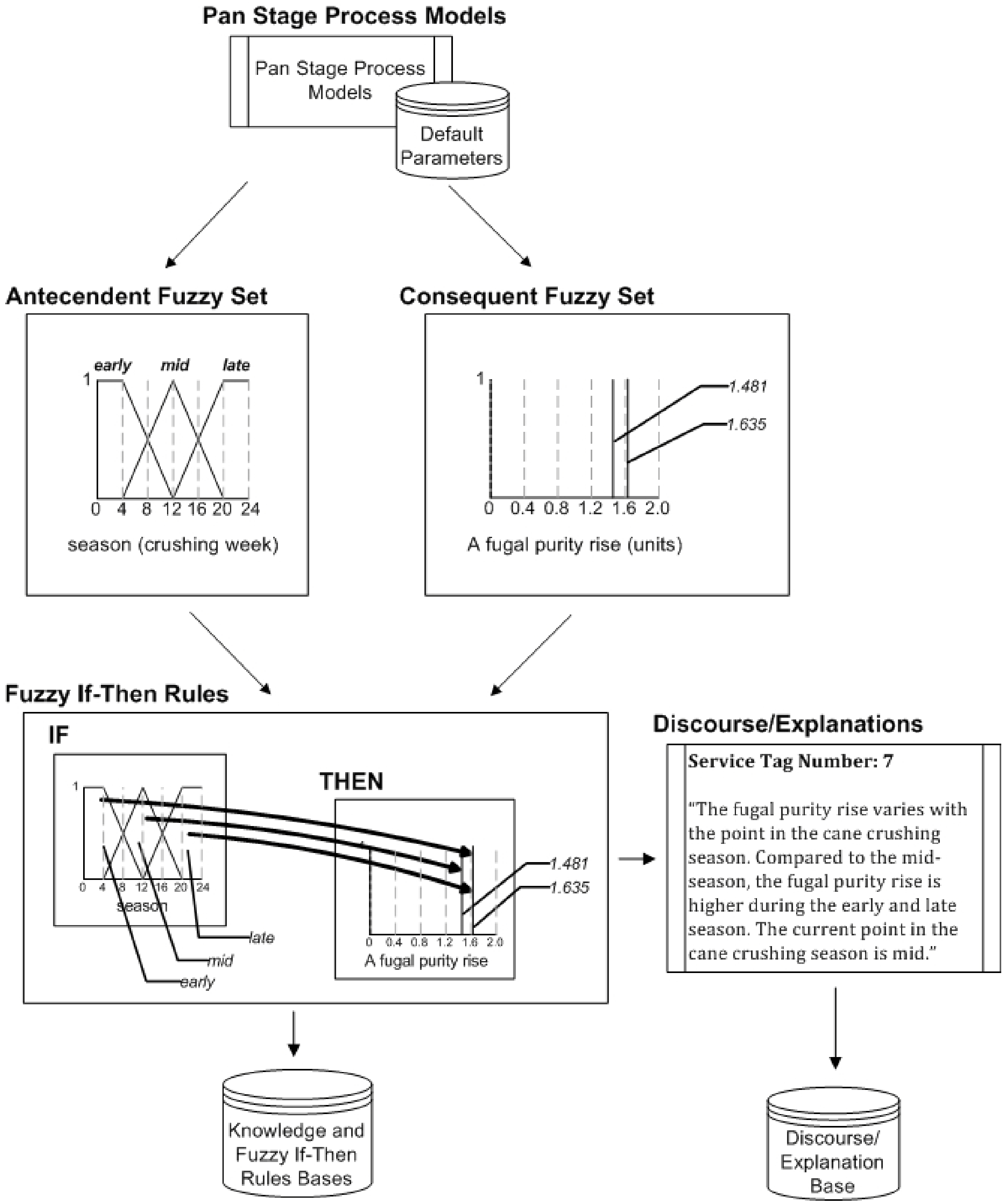

Figure 39: An overview of the knowledge acquisition process

6.4.1 Method of Testing

In order to validate the modelling approach in relating the sections of the sugar factory to the pan stage, and in modelling the internal workings of the pan stage, stock tank levels are used. The stock tank predictive models unify:

- syrup prediction model;
- steady state pan stage flow model;
- empirical vacuum pan models;
- vacuum pan phase determination and forecast model;
- dynamic allocation of predicted quantities to forecast intervals algorithm;
- blackboard system; and
- fuzzy logic pre-processing and post-processing adjustments to account for real world operating conditions.

The comparison of KBSSS simulated results to stock tank data is used to validate the fundamental modelling approach and to demonstrate the viability of the predictions and the underlying modelling approach of using boil-on rate models of pan stage feed materials in conjunction with pan stage schedule and feed material return rates.

Stock tank levels were recorded by the Racecourse sugar mill (Mackay, Queensland) Citect control system over the period over 03/09/2003 and 04/09/2003 on a 30 second interval basis along with the key process variables required for the pan stage process models developed in Section 5.2. A simulation was performed for the time of 11:45PM on 03/09/2003 over an eight hour time forecast horizon with a resolution of 15 minute discrete intervals during this prediction period. This simulation utilised control system data for the time period leading up to 11:45PM 03/09/2003.

Hypothetically under ideal circumstances prediction from the KBSSS over the forecast period should be similar to the levels displayed by the control system data for the stock tank levels. Of key importance are the *peaks* and *troughs* that would occur in the tank levels during pan stage operations. The prediction of stock tank level *peaks* and *troughs* for level prediction are of key significance. Normal factory operation is prevented during stock tank overflow or empty conditions and serious remedial actions are required. These scenarios occur at stock tank level *peaks* and *troughs* and should be avoided.

The following sections will describe each of the major test components with reference to the consultation process undertaken by the end user.

6.4.2 Consultation Process: Input

The consultation process is undertaken by the end user of the KBSSS. Due to the relatively slow change in real world operating condition to be supplied the consultation process is not a time consuming process and requires relatively limited maintenance of information in providing KBSSS consultation updates on information of real world operating conditions. The continuous processing nature of pan stage operations and the nature of KBSSS support in offering advice means that the consultation input required for the current KBSSS processing regime should be relatively similar to the previous.

Conducive to the fuzzy variables and their universe of discourse the following information may be required to be supplied as part of the consultation process, dependant upon their change since the previous consultation process was performed. These parameters influence the future prediction of the pan stage operation conditions. In order to undertake the prediction regime the following parameters may be required as part of the inference process supported by fuzzy pre-processing and post-processing functionality working in tandem with the industrial pan stage process models and system explanatory capabilities:

1. Current progression point through the cane crushing season;
2. For each receiver, expected time delay after pan drop until fugalling commences;
3. For each vacuum pan, the equipment performance rating of each vacuum pan (i.e. scaled tubes, vacuum leaks);
4. The crystallisation characteristic factor for A molasses, B molasses and syrup feed materials; and
5. Syrup purity data from the daily laboratory analysis.

These factors are assumed to be relatively straight forward knowledge from pan stage operator experience and this information able to be readily acquired. In the event of unknown values the KBSSS can default to pre-determined values. This is one of the fundamental advantages and a credit to the fuzzy logic based approach. System stability and robustness can be maintained even in the absence of unknown data and without degrading system performance. Additionally several of these parameters can be sourced elsewhere or approximated through additional means. The current point in the season can be approximated using the current KBSSS system date and an approximation for the expected cane crushing season duration. Using the *locality of reference principle* syrup purity data can default to the previous days recorded value if unknown.

Once this data is supplied by the end user, and in line with the blackboard scheduling component directives, the interaction of the pan stage process models will be undertaken along with the retrieval and activation of the inference process for the fuzzy If-Then rules as part of pre-processing and post-processing localisation adjustments. User supplied data is iteratively matched against the fuzzy rules as part of the inference process and control system data, drawn from external parasitic external factory data sources, is utilized by the industrial pan stage process models. As a result of the pre-processing localisation adjustments carried out by the fuzzy rules, input model parameters are adapted. Process model outputs are similarly adapted as part of the post-processing process with defuzzification occurring on results of the inference process to yield crisp output values. This localisation adaption refines the pan stage process models to account for real world external conditions that is not part of the predefined static knowledge bases. Storage of working results used during the process of formulating the prediction of future pan stage operating conditions occurs with the blackboard system presented in Section 5.3.2. The final inferred results are then passed to the output layer for formatting and presentation.

6.4.3 Consultation Process: Output

Upon completion of the inference processes, pan stage process model processing, prediction of future pan stage operating conditions and explanatory subsystem processing, final results are consolidated to be displayed by the KBSSS output layer. For the test case simulation, the system results will be presented to the end user and composed of several key elements. Each of these elements corresponds to the primary and secondary outputs as detailed for the output layer specifications and requirements presented in Section 4.2. The KBSSS presents its advice and recommendations to end users through graph and diagram display and tabular format supported by explanatory supporting information.

In the following sections, the KBSSS simulated test results will be provide output consisting of the following elements. These elements forming the primary and secondary system outputs are as follows:

1. Control strategies (primary output);
2. Prediction of future pan stage operating conditions (secondary output); and
3. Explanatory discourse and justifications supporting the above elements (secondary supporting output).

The purpose of each of these elements and how they are generated will be detailed in the following sections.

6.4.4 Primary Output: Control Strategies

Pan stage control requires the operational management of multiple vacuum pans operating concurrently to a repetitive schedule and the maintenance of sugar crystal growth characteristics, along with the management of feed material stocks. The pan stage interacts with the juice processing section of the sugar factory and the centrifugal stations and has incoming process materials from these segments of the factory. These interactions must also be managed.

The strategic management and control requirements for pan stage operations and the fundamentals of the sugar boiling process has been well documented in literature (Frew and Wright, 1976; Frew and Wright, 1977; Wright, 1983; Miller and Broadfoot, 1997; Beath and Miller, 2000; Miller and Beath, 2000; Broadfoot and Pennisi, 2001; Sugar Research Institute, 2001).

The four core control strategies for the primary KBSSS system output are:

- **Pan duty management.** This strategy involves defining the most appropriate duties for "swing" vacuum pans that may have multiple possible massecuite production duties. The management task is to match the required A/B massecuite production ratio and also to ensure adequate quantities of A molasses and B molasses are maintained in stock.

- **Pan control strategy.** Due to the sugar crystal volumetric growth limitations on vacuum pans and requirements for multiple successive pan strikes for sugar crystal growth (Wright, 1983), the footing quantities provided at the seed creation stage of the process plays a pivotal role in the size of the final product sugar crystals. As part of this management strategy steam usage rates also affect the pan strike duration and must be accounted for to ensure that it *meshes* into the pan stage schedule.

- **Pan schedule management.** This strategy requires management of vacuum pans to ensure that they *mesh* into the pan stage boiling schedule and interact together while maintaining continuous operation and repetitive cycles. This requires the scheduling of pan strike start time and pan drop time with adequate time for pan preparations. Only modifications to the length of the *legs* in the pan stage schedule is undertaken.

- **Stock tank management.** This strategy involves the management of levels of liquor, A molasses and B molasses to ensure there is adequate quantities in stock for processing operations. Adequate stock tank materials must be maintained to avoid conditions of empty or overflow. Directed actions for the other control strategies influence the projected stock tank level outcomes. Management of stock tank levels to avoid remedial conditions is a fundamental requirement of the KBSSS specifications.

These control strategies are the primary tasks undertaken by pan stage operators and KBSSS output in each of these key areas will aid in pan stage operator decision making strategies.

6.4.4.1 Representation for Control Strategies

Due to the concise nature of the control strategy output, quantitative data pertaining to the above mentioned control strategies are presented. In the provision of this capability, the KBSSS employs a tabular representation to conveniently express the intended control actions and strategies to the end users. Given the complex nature of the KBSSS only a simple data presentation is required for final control strategy output. The complexity of the KBSSS is through the underlying functionality required in arriving at these recommendations. The recommendations themselves are relatively straight forward control actions required to be undertaken by the pan stage operators. Final results of the KBSSS are control actions that the operators perform in conjunction with existing pan stage control system infrastructure as depicted in Figure 3. The embedding of the KBSSS into existing infrastructure is detailed in Chapter 7.

Each control strategy is listed sequentially in a table format. For each of these strategies the tuple representing a row in these tables is described:

Swing Pan Duty {Vacuum Pan Number, Duty, Expected Strike Start Time}

where,

Vacuum Pan Number *is the number uniquely identifying the vacuum pan,*

Duty *is either the task of "A" or "B" massecuite production,*

Expected Strike Start Time *is the date/time combination signifying the expected time that the strike will commence.*

This signifies the duties for the defined vacuum pan. Since vacuum pans run continuously around the clock processing the expected strike start time indicates the strike that the duties are to be assigned to.

Pan Schedule {Vacuum Pan Number, Strike Start Time, Strike Drop Time}

where,

Vacuum Pan Number *is the number uniquely identifying the vacuum pan,*

Strike Start Time *is the date/time combination signifying the expected time that the strike will commence,*

Strike End Time *is the date/time combination signifying the expected time that the strike will drop.*

This representation matches the vacuum pans with expected strike start and completion times in order to mesh with the proposed schedule of operations.

Steam Rate {Vacuum Pan Number, Start Time, End Time, Steam Rate}

where,

Vacuum Pan Number *is the number uniquely identifying the vacuum pan,*

Start Time *is the date/time combination signifying the expected time that the strike will commence,*

End Time *is the date/time combination signifying the expected time that the strike will drop,*

Steam Rate *is the rate (t/h) of steam projected to be required for the pan to fill its production duties within the required time period to mesh into the pan stage schedule.*

This relationship signifies the steam rate required for the vacuum pan between two defined time points in the schedule.

Seed Pan Footing Quantity {Vacuum Pan Number, Footing Quantity, Expected Strike Start Time}

where,

Vacuum Pan Number *is the number uniquely identifying the vacuum pan,*

Footing Quantity *(t) is required quantity of footing material required for the vacuum pan,*

Expected Strike Start Time *is the date/time combination signifying the expected time that the strike will commence.*

This signifies the required footing quantity for the defined vacuum pan. The particular strike is identified by its starting time.

Nett Stock Tank Levels {Type, Initial Level, Prediction Horizon, Sum of Feed Material Quantities, Sum of Return Material Quantities, Projected Final Level, Maximum Occurring Level, Time of Maximum Occurring Level, Minimum Occurring Level, Time of Minimum Occurring Level}

where,

Type *is the feed material type of the stock tank,*

Initial Level *(t) is the current quantity of stock material within the tank,*

Prediction Horizon *is the period over which the forecast was made,*

Sum of Feed Material Quantities *(t) is the quantity of feed materials taken from the stock tank over the prediction horizon,*

Sum of Return Material Quantities *(t) is the quantity of materials being fed back to the stock tank over the prediction horizon,*

Projected Final Level *(t) is the projected stock tank level at the end of the prediction horizon period,*

Maximum Occurring Level *(t) is the maximum occurring quantity over the prediction horizon period,*

Minimum Occurring Level *(t) is the minimum occurring quantity over the prediction horizon period,*

Time of Maximum Occurring Level *is the date/ time combination that the maximum stock tank level have occurred at within the prediction horizon period,*

Time of Minimum Occurring Level *is the date/ time combination that the minimum stock tank level have occurred at within the prediction horizon period.*

Over the projected forecast horizon data pertaining to the points at which the maximum and minimum tank levels occurred along with the sum of both the feed and return material quantities is collated. The initial stock tank level along with projected final level is also presented.

6.4.5 Supporting Output: Prediction of Future Operating Conditions and Explanatory Capabilities

As presented in the previous sections, the KBSSS's primary output is supported by two other supporting outputs which provide a prediction of future pan stage operating conditions and explanatory discourse to explain and justify the outcome of the primary outputs. The following subsections detail the operation of these two outputs.

6.4.5.1 Generating the Prediction of Future Pan Stage Operating Conditions

The pan stage process models are used to generate a forward prediction of future pan stage operating conditions. These process models are chained together in a hierarchical structure due to the data dependencies that exist between them. Fuzzy logic provides pre-processing and post-processing localisation adaption to account for real world operating conditions that are not part of the KBSSS knowledge bases. This approach provides adaption for the process models based upon the specified fuzzy If-Then rules. The individual process models run as presented in Section 5.2. The fuzzy logic pre-processing and post-processing adaptive processes function as specified in 5.4.3. The scheduling of these processes, in accordance with the data dependencies that exist between the process models, is undertaken by the scheduling component of the blackboard system presented in Section 5.3.2.

This scheduling of the pan stage process models is depicted in Figure 27 with the fuzzy logic based pre-processing and post-processing localisation adjustments performing as presented in Figure 34. The overall prediction methodology adhered to in generating the prediction of the future pan stage operating conditions is presented in Section 5.4.4.1

Intermediate and final results are stored by the blackboard data repository system. Collectively the pan stage process models and the fuzzy inference system utilze databases storing information on dynamic user consultation data, sugar mill control system data, blackboard system data, knowledge base, fuzzy If-Then rule base, process model default parameter database and explanatory discourse knowledge base.

6.4.5.2 Representation for the Prediction of Future Operating Conditions

Based upon the prediction procedures outlined in the previous section, a forward forecast is built across the forecast horizon based upon existing conditions. Final blackboard system data, resulting from the pan stage process models working in tandem with the fuzzy If-Then rules, is formatted to a graphical representation.

The pan stage process models resulting in graphical output layer elements are the:

1. syrup prediction model;
2. pan stage steady state flow model; and
3. stock tank prediction models for liquor, A molasses and B molasses feed materials.

The prediction of future operating conditions is done through a series of graphical displays. Recall from Section 5.2 that the empirical vacuum pan models essentially consist of a database lookup scheme of previously developed models and that the vacuum pan phase detection and forecast model provides background support in building results for the stock tank models. The schedule optimisation model uses the developed pan stage steady state flow model as the fundamental supporting feature to enable the provision of control actions and advice. Results of these supporting models do not form part of the prediction process formatted output.

Results from the syrup prediction model are presented in graph format with a time scale axis plotting against predicted quantities utilizing standard line chart formatting. The projected sucrose and impurity quantities over the forecast period are displayed as well as the combined total quantity. Since this model predicts the solids flow amounts to the pan stage, the resulting total solids quantities are also converted into actual occurring quantities.

The pan stage steady stage flow model implements a compact representation of Figure 13 with alternative views for both solids flows and actual flows. Information on flows and purities are presented along with key crystal content and dry substance measures for the process material flows are provided. Due to the large quantity of data generated by this process model, a compact representation is used to convey results. Pan stage equipment items are merged together for easier representation with the major process purities and flows indicated against each device.

Stock tank model results for liquor, A molasses and B molasses feed materials are presented in a similar representation to results from the syrup prediction model. Predicted tank level quantities are plotted against a time scale over the prediction period.

6.4.5.2 Generating Explanations

The technique for enabling explanatory capabilities was presented in Section 5.5 using an adapted version of the REST3 method (Chiou and Yu, 2007a). This system uses a linear based trace system using rule tags and trace tables in conjunction with the inference process. Predefined explanations, tagged to fuzzy If-Then rules, are generated when the fuzzy rules exceed defined degree of fulfilment measures during the inference process. These mechanics generate active supporting advice that are used to provide support for the test case results and are presented to help support the KBSSS output.

This technique is not an intelligent system approach. Instead it uses simple tagged explanations to provide the supporting explanations and justifications. Within the following simulated test, the generated explanations are using to support the primary system output. Working in tandem with the primary supporting advice the generated explanations provides comprehensive information.

6.5 Test Results

In the following test results, comparisons will be made between predictions undertaken by the KBSSS process as outlined in Section 5.4.4 of the thesis and actual occurrences based upon data from sugar mill control system data. Some subjectivity is required in assessing control system recommendations. Further factory trials are envisaged as part of follow on research for validation of offered output and recommendations.

To facilitate the evaluation of the simulated results in comparison to actual occurrences, the reader is to note that the primary goal of the simulation is to assess whether the KBSSS can provide *reasonable* prediction of future operating conditions given the absence of existing pan stage forecast methods. Recall from Chapter 2 the current lack of existing modelling approaches available to relate together the sections of the sugar factory in order to forecast future pan stage operating conditions. Advice and recommendations are based upon the KBSSS forecast mechanics to provide support for end users in the pan stage decision making process.

Racecourse sugar mill simulated predictions were made for an 8 hour forward prediction period for the point in time of 11:45PM on 03/09/2003. Data leading up to this point is also used in generated a forecast of the future pan stage operating conditions. This point in time was chosen as allows for a mid-point of prediction given the two days of available control system data.

6.5.1 Input Data

Both sets of data from the human end users and the KBSSS were based upon conditions existing at the time the forecast was performed. All relevant data was entered into the KBSSS to initiate the consultation process. Data for testing was supplied by Racecourse sugar mill (located in Mackay, Queensland) for the days of 03/09/2003 and 04/09/2003. Data before the prediction period is used in the forecast period and validated with control system data from after this point. Details of the control system data sources and input information are presented in Appendix D.

The end user data supplied to the KBSSS were based upon real world information existing at the time of the prediction. A summary of these is:

1. **Point through the cane crushing season.** Current progression point through the cane crushing season. At 03/09/2003 the cane crushing season was mid-way through;

2. **Fugalling delay after pan drop**. For each receiver, the expected processing delay after pan drop until fugalling of the massecuite could occur. This was dependant upon the fugalling section operations and occurring wait times for dropping pans to receive fugalling of their massecuite that has been placed in receivers;

3. **Equipment performance rating**. For each vacuum pan, the equipment performance rating of each vacuum pan. All vacuum pans on the pan stage were operational and

in excellent working order with no operational problems such as vacuum leaks or scaled surfaces reported;

4. **Crystallisation characteristic factor**. The crystallisation characteristic factor for A molasses, B molasses and syrup feed materials. Crystallisation characteristics of the feed material streams were excellent. Stand over cane was not being processed at the time; and

5. **Syrup purity data.** Syrup purity data from the daily laboratory analysis. The syrup purity value was measured in laboratory shift analyses on 03/09/2003 and determined to be 89%.

6.5.2 Control Strategies

With discretisation into 15 minute prediction intervals and mid-season conditions focusing on pan stage productivity as depicted in Figure 23 evaluations were undertaken for schedule strike durations of 3.5 hours, 3.25 hours and 3 hours. The pan stage high grade schedule was considered with the assumption that steam rates for low grade pans were fixed and subsequently did not enter into calculations. Major model inputs featured the average syrup production rate and purity from the syrup prediction model. Results for the syrup prediction model are detailed in 6.5.3.1. Based upon the schedule optimisation process detailed in Section 5.2.6 and the profit function detailed in Equation (5.6) the following values were used in the evaluation of the three schedule strike durations:

1. product sugar was valued at $300 per tonne,
2. final molasses was valued at $60 per tonne; and
3. steam was valued at $6 per tonne.

The premium sugar bonus under the defined schedule strike durations was as defined in Figure 23. Results of the schedule optimisation process are presented in Table 12.

The sugar premium bonuses combined with the reduced steam consumption rates in Table 12 results in higher profit per on a normalised per hour basis and indicates a longer schedule strike cycle duration under current operating conditions is favourable. A schedule strike cycle duration of 3.5 hours results in a normalised hourly profit of $4414.44 for the previously defined profit function.

Schedule Optimisation Data	Schedule Cycle Duration (h)		
	3.00	3.25	3.50
Product Sugar Rate (t/h)	16.27	16.35	16.45
Product Sugar Quantity (t)	48.810	53.138	57.575
Final Molasses Rate (t/h)	7.46	7.22	6.97
Final Molasses Quantity (t)	22.380	23.465	24.395
C Sugar Footing Rate to A Seed Pan(t/h)	1.06	1.06	1.05
C Sugar Footing Rate to B Seed Pan(t/h)	0.85	0.85	0.86
C Sugar Quantity (t)	6.208	6.685	7.163
Sugar Premium Bonus ($)	0.000	1.375	2.750
Steam Quantity Usage (t)	648.00	611.00	574.00
Profit ($)	12097.800	13756.214	15450.531
Normalised Hourly Profit ($)	4032.600	4232.681	4414.438

Table 12: Results of the schedule optimisation for the forecast time of 11:45PM 03/09/2003

High grade seed vacuum pan number 1 is used as the basis for undertaking the new schedule as this is the initial growth pan for the high grade schedule. From the schedule optimisation algorithm this pans most recent strike commencement prior to the prediction point of 11:45PM 03/09/2003 was at 9:59PM 03/09/2003. Using the empirical pan models as reference the next strike determined to commence at 12:33AM 04/09/2003. The schedule optimisation model builds a future schedule of operations with defined strike cycle duration of 3.5 hours commencing from this point with recommendation of vacuum pan steam rates to meet this schedule. A compact representation of the generated schedule is presented in Figure 40.

Under this schedule, the pan commencement and drop points for the high grade section of the pan stage are specified along with recommendations of swing pan duties for batch vacuum pans number 2 and 9. The time offset for scheduled duties, based upon a commencement of initial high grade seed pan number 1 at 12:33AM 04/09/2003, is presented in Figure 40. Based upon this schedule and results of the optimisation process the following control strategies are advised. Swing pan duties are presented in Table 13, the individual vacuum pan schedule is presented in Table 14, steam rate requirements for batch vacuum pans to mesh into the schedule is presented in Table 15, seed pan footing quantities are presented in Table 16.

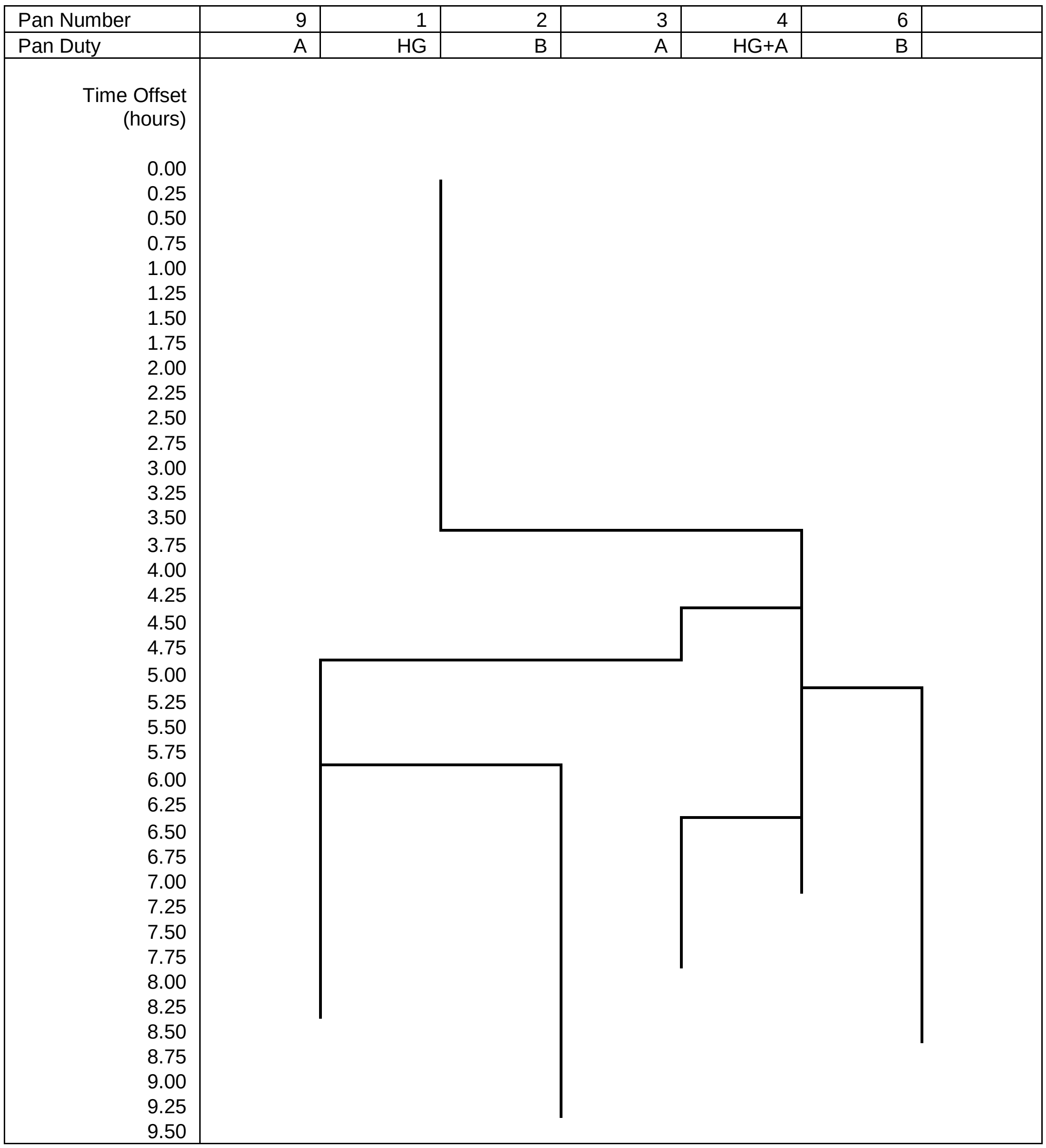

Figure 40: Optimised schedule with a fixed strike cycle duration of 3.5 hours

For the recommended control system strategies data pertaining to the next recommended pan strike, under the optimised schedule with pan strike cycle duration of 3.5 hours, only control actions for the next occurring pan strike has been presented. This is to aid in clarity of output. Strike times after this point however are readily calculated due to the repetitive nature of strikes. An allowance of 15 minutes (minimum defined schedule resolution period) must be allowed between the strike cycle durations for the vacuum pan *steam out* preparation phase before a subsequent pan strike can occur. Strike durations remain unchanged.

The 15 minute interval for pan clean up and preparation for subsequent strikes takes the elementary pan cycle duration of the schedule to 3.75 hours which is the duration required for a cycle to repeat itself. Using this time interval the footing quantities to batch vacuum pan number 1, performing high grade seed duties, the hourly rate of C sugar return feed rates to the A and B seed pan from the modified steady state pan stage flow model are summated. Racecourse sugar mill uses batch vacuum pan number 1 collectively for high grade seed operations. There is no separate A seed and B seed preparation duties as presented in Figure 13 so the C sugar footing return rates are merged over the elementary pan cycle duration.

A summary of the stock tank level prediction undertaken for the point of 11:45PM 03/09/2003 is also presented in Table 17. Detailed results for this management data are presented in Section 6.5.3.3. The presented data summary provides a reference for critical projected *peak* and *trough* level times during pan stage operations over the forecast horizon. Highlighting these times of concern can aid in forewarning pan stage operators of potential future operational problems with stock tank levels.

Vacuum Pan Number	Duty	Expected Strike Start Time
2	A Massecuite	6:18AM 04/09/2003
9	B Massecuite	5:18AM 04/09/2004

Table 13: Swing pan duties for the optimised schedule with a fixed strike cycle duration of 3.5 hours

Vacuum Pan Number	Strike Start Time	Strike Drop Time
1	12:33AM 04/09/2003	4:03AM 04/09/2003
2	6:18AM 04/09/2003	9:48AM 04/09/2003
3	4:48AM 04/09/2003	8:18AM 04/09/2003
4	4:03AM 04/09/2003	7:33AM 04/09/2003
6	5:33AM 04/09/2003	9:03AM 04/09/2003
9	5:18AM 04/09/2003	8:48AM 04/09/2003

Table 14: Individual vacuum pan schedule for the optimised pan stage schedule with a fixed strike cycle duration of 3.5 hours

Vacuum Pan Number	Start Time	End Time	Steam Rate (t/h)
1	12:33AM 04/09/2003	4:03AM 04/09/2003	25
2	6:18AM 04/09/2003	9:48AM 04/09/2003	32
3	4:48AM 04/09/2003	8:18AM 04/09/2003	25
4	4:03AM 04/09/2003	7:33AM 04/09/2003	25
6	5:33AM 04/09/2003	9:03AM 04/09/2003	32
9	5:18AM 04/09/2003	8:48AM 04/09/2003	25

Table 15: Steam rates required for vacuum pans to mesh into the pan stage schedule with a fixed strike cycle duration of 3.5 hours

Vacuum Pan Number	Footing Quantity (t/h)	Expected Strike Start Time
1	7.163	12:33AM 04/09/2003

Table 16: Seed pan footing quantities required for the pan stage schedule with a fixed strike cycle of 3.5 hours

Type	Syrup	A Molasses	B Molasses
Initial Level (t)	121.05	66.66	94.37
Prediction Horizon (h)	8	8	8
Sum of Feed Material Quantities (t)	607.99	457.07	185.19
Sum of Return Material Quantities (t)	683.33	457.58	221.66
Projected Final Level (t)	196.39	67.17	130.84
Maximum Occuring Level (t)	215.78	168.38	140.19
Time of Maximum Occuring Level	7:15AM 04/09/2003	1:00AM 04/09/2003	5:30AM 04/09/2003
Minimum Occuring Level (t)	23.10	50.77	76.37
Time of Minimum Occuring Level	1:15AM 04/09/2003	2:45AM 04/09/2003	3:00AM 04/09/2003

Table 17: Projected stock tank data for the stock tank level forecast undertaken for the time of 11:45PM 03/09/2003

6.5.3 Prediction of Pan Stage Operating Conditions

The following sections detail results of the prediction of future pan stage operating conditions based upon the initial pan stage operating conditions at and leading up to 03/09/2003 11:45PM, as identified earlier. In establishing a prediction of future pan stage operating conditions a forecast of syrup quantities to the pan stage, steady state flows of process material quantities and purities and stock tank levels of vacuum pan feed materials is determined.

6.5.3.1 Syrup Prediction Model

A 90 minute forward forecast of sucrose and impurity quantities loadings to the pan stage was built as part of the KBSSS prediction process as presented in Section 5.4.4. This prediction was made for Racecourse sugar mill (Mackay, Australia) cane rake data at 11:45PM on 03/09/2003 for information specific to the 2003 cane crushing season. Further information on Racecourse sugar mill data information sources is presented in Appendix D. This prediction is based upon the cane rake data in the 96 minute period prior to 03/09/2003 11:45PM. A 96 minute time frame is used when establishing valid cane rake data for the prediction period as this is the approximate time it takes syrup from crushed cane to reach the pan stage.

Cane quantities were measured at the cane receival station while pol%cane was calculated from juice laboratory analysis of the first expressed juice sample. The syrup purity value was measured in laboratory shift analyses on 03/09/2003 and determined to be 89%. The empirical operational factory fraction used was established in previous research (Dodd, Broadfoot, Yu and Chiou, 2005a) and set as 0.9725 for Racecourse sugar mill, as determined in Appendix A.

Using the previously presented prediction methodology, sucrose and impurity quantities were allocated to the intervals shown in Table 18 and Table 19 respectively. The break down of sucrose and impurity quantities to each 15 minute interval over the forecast horizon is presented with reference to the logical rake numbers identified within the previous 96 minute interval from cane receival data. Recall from Section 5.3.1 the use of the dynamic allocation algorithm to apportion batch quantities to interval durations over the forecast period. The predicted sucrose and impurity quantities allocated use the syrup prediction model presented in Section 5.2.1. When summated these quantities indicate the expected syrup solids quantity to the pan stage after cane crushing.

A collation of results from Table 18 and Table 19 is presented in Table 20 with conversion of the expected syrup solids total provided as actual real world quantities. The total quantity of syrup is the quantity of solids, taken as the sum of sucrose and impurities, excludes the quantity of water that is present in practice.

	Impurity quantity allocated (t) to time interval						
Logical Rake Number	11:45 PM	12:00 AM	12:15 AM	12:30 AM	12:45 AM	1:00 AM	1:15 AM
1	0.54	0.40					
2		1.85	0.46				
3			1.45				
4			0.17	1.82			
5				0.62	1.86		
6					0.62	0.91	
7						0.10	
8						0.63	
9						0.73	1.76
10							0.60
Total Impurities (t)	0.54	2.25	2.08	2.44	2.48	2.37	2.36

Table 18: Breakdown of impurity quantities for syrup prediction model made at 03/09/2003 11:45PM using the dynamic allocation model

	Sucrose quantity allocated (t) to time interval						
Logical Rake Number	11:45 PM	12:00 AM	12:15 AM	12:30 AM	12:45 AM	1:00 AM	1:15 AM
1	4.37	3.28					
2		14.94	3.74				
3			11.70				
4			1.34	14.72			
5				5.01	15.04		
6					3.67	7.34	
7						0.82	
8						5.11	
9						5.92	14.21
10							4.86
Total Sucrose (t)	4.37	18.22	16.78	19.73	18.71	19.19	19.07

Table 19: Breakdown of sucrose quantities for syrup prediction model made at 03/09/2003 11:45PM using the dynamic allocation model

Prediction Time	Sucrose Quantity (t)	Impurity Quantity (t)	Total Solids (t)	Actual Quantity (t)
11:45:00 PM	4.37	0.54	4.91	7.22
12:00:00 AM	18.2	2.3	20.5	30.1
12:15:00 AM	16.8	2.1	18.9	27.7
12:30:00 AM	19.7	2.4	22.2	32.6
12:45:00 AM	18.7	2.5	21.2	31.2
1:00:00 AM	19.2	2.4	21.6	31.7
1:15:00 AM	19.1	2.4	21.4	31.5

Table 20: Summary of prediction quantities for syrup prediction model made at 03/09/2003 11:45PM using the dynamic allocation model

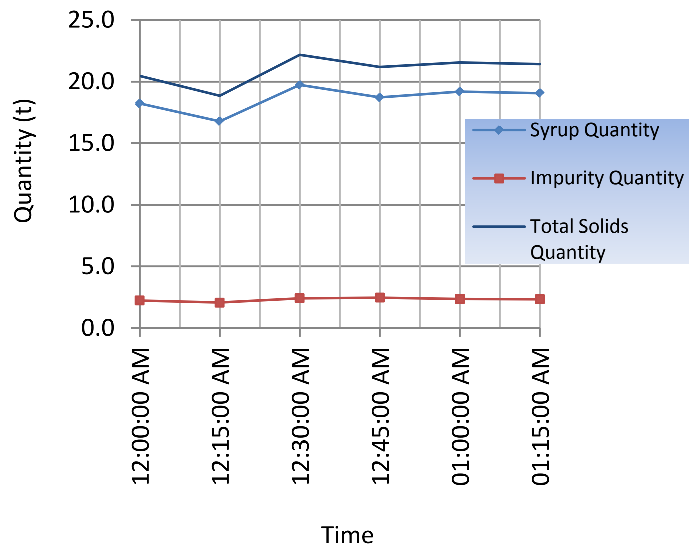

Figure 41: Solids flow quantity results from the syrup prediction model at 03/09/2003 11:45PM

The sucrose and impurity quantities from Table 20 along with the total syrup solids are presented in Figure 41 with the final predicted syrup quantities presented in Figure 42. The syrup production rate is very consistent at approximately 31 tons of syrup being delivered to the pan stage at each 15 minute interval as a result of the crushing and juice processing operations undertaken on cane rakes received by the sugar factory in the 96 minutes

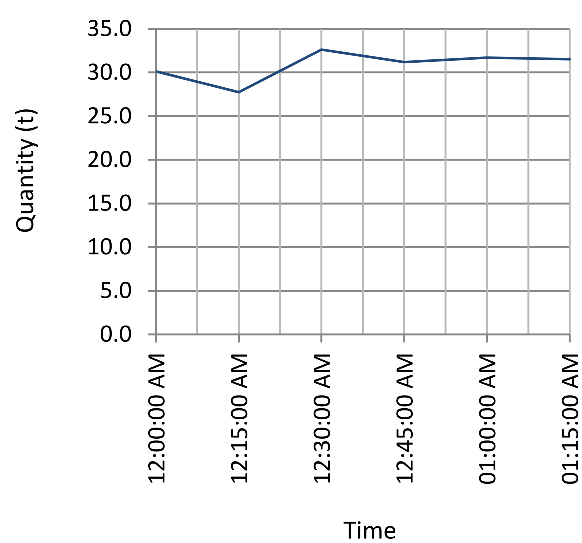

Figure 42: Predicted syrup flow quantity results from the syrup prediction model at 03/09/2003 11:45PM

leading up to the prediction performed for 03/09/2003 11:45PM.

Measurements of factory control system data in the case for syrup production rates were unable to be obtained for the 2003 cane crushing season due to inadequate factory instrumentation calibration. Recall that the derivation of the syrup prediction model and its predictive performance is presented in Appendix A.

6.5.3.2 Pan Stage Steady State Flow Model

Syrup forms the primary input to the pan stage steady state flow model. The average syrup production quantity values are used from syrup prediction model in line with the data dependencies exhibited in Figure 28 and the prediction methodology detailed in Section 5.4.4. The default parameters for the flow model were listed in Section 6.3.1. Validation of the pan stage steady state model approach is presented in Appendix C with test results compared against a reference model from pan stage research (Broadfoot and Pennisi, 2001).

Final results of the pan stage steady state model are the prediction of long term production rates of process materials, product sugar and final molasses. Determination of C sugar footings rates required for seed pans along with quantification of the long term remelt rate to the syrup tank are also generated. Due to the large volume of model data results generated, a streamlined representation of the key process material solids flows and their associated purities is presented in Figure 43. The overall layout is similar to the overall model schematic shown in Figure 13. In this reduced representation certain equipment items and their associated flows have been clustered together for a compact results display. Total process material flows and purities are presented in Figure 44.

For the results presented in Figure 43 and Figure 44, a summary of process material flows is presented in Table 21 with purities of these process material flows presented in Table 22. The presented results allow for the quantification process material flows for interactions of pan stage process with the juice processing and centrifugal sections of the sugar mill. This provides a determination of the long term pan stage production rates and purity measures. Specifically these results quantify the C sugar footing quantities to seed pans, long term

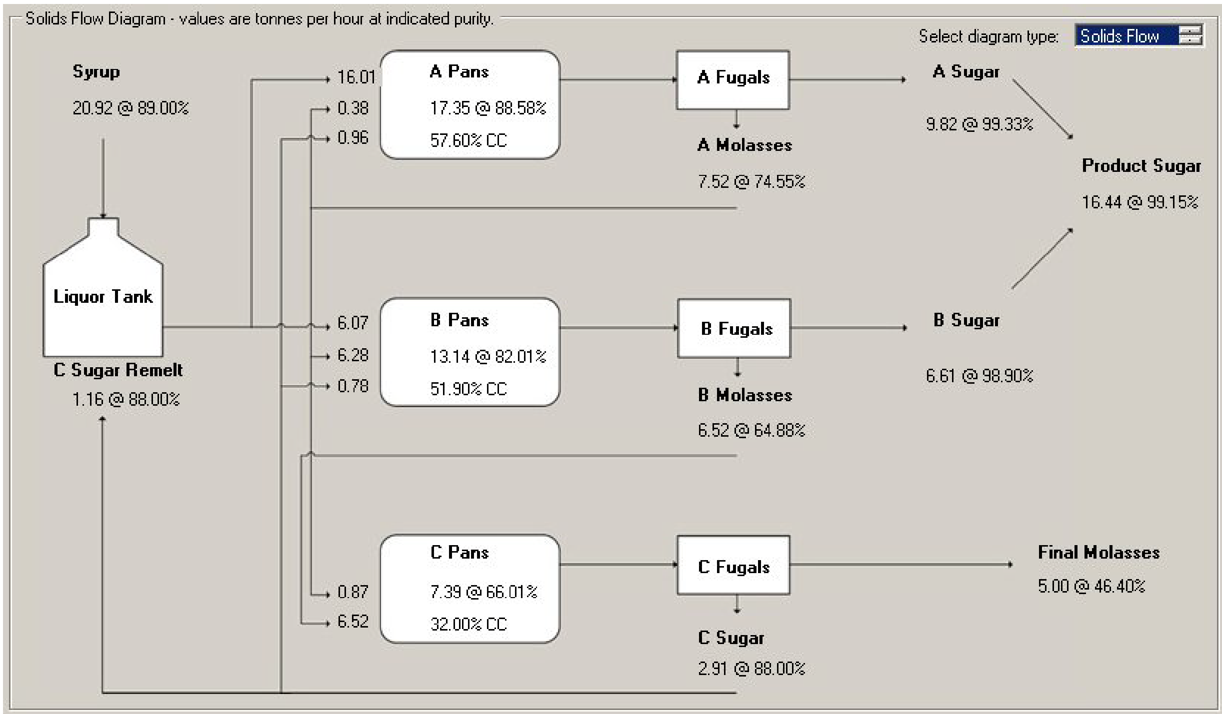

Figure 43: Solids process material flow results from pan stage steady state flow model

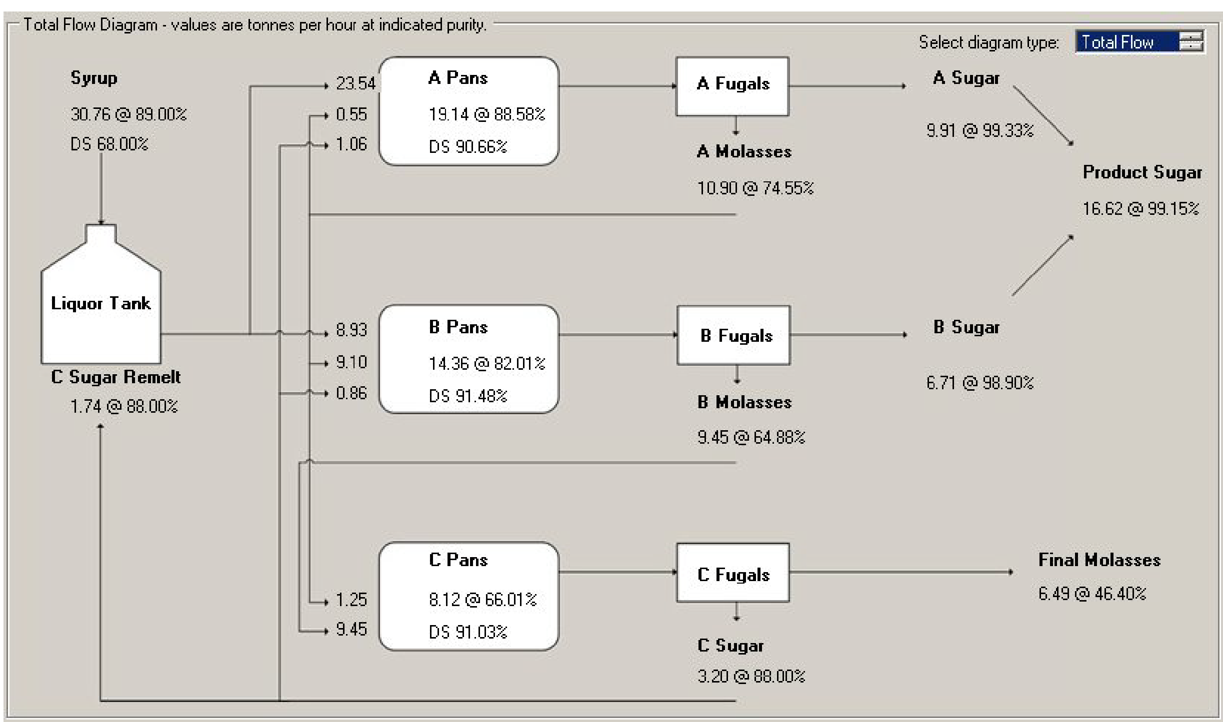

Figure 44: Total process material flow results from pan stage steady state flow model

production rates of product sugar, final molasses and C sugar remelt rates for use in liquor tank level prediction.

Flow from	Flow to	Solids flow (t/h)	Actual flow (t/h)
Liquor Tank	A Pans	16.01	23.54
Liquor Tank	B Pans	6.07	8.93
A Fugals	A Pans	0.38	0.55
A Fugals	B Pans	6.28	9.1
A Fugals	C Pans	0.87	1.25
B Fugals	C Pans	6.52	9.45
C Fugals	A Pans	0.96	1.06
C Fugals	B Pans	0.78	0.86
A Fugals	A Sugar	9.82	9.91
B Fugals	B Sugar	6.61	6.71
A/B Sugar	Product Sugar	16.44	16.62
C Fugals	Final Molasses	5.00	6.49
A Pans	A Fugals	17.35	19.14
B Pans	B Fugals	13.14	14.36
C Pans	C Fugals	7.39	8.12

Table 21: Steady state flow model process material predicted solids flows and conversions to actual flows

Flow from	Purity (%)
Liquor Tank	88.94
A Pans	88.58
B Pans	82.01
C Pans	66.01
A Fugals	74.55
B Fugals	64.88
C Fugals	88.00
A Sugar	99.33
B Sugar	98.90
Product Sugar	99.15
Final Molasses	46.40

Table 22: Steady state flow model process material flow purities

6.5.3.3 Stock Tank Level Prediction Models

Stock tank level modelling applies the techniques for prediction detailed previously. Prior thesis supporting research (Dodd, Broadfoot, Chiou and Yu, 2008b) has detailed the approach used in stock tank level modelling. The stock tank level predictions are based upon the initial conditions at and leading up to 11:45PM 03/09/2003 with a forecast made over the following eight hour period.

The results of the prediction process are presented in Table 23 with predicted stock tank level values presented against the actual occurrences along with the differences between these sets of values. Racecourse sugar mill control system data was used as the reference for stock tank levels occurring at the prediction times. The corresponding graphs of syrup, A molasses and B molasses stock tank level predicted values along with actual occurring level values are plotted in Figure 45, Figure 46 and Figure 47 respectively.

Results from the syrup, A molasses and B molasses tank level predictions trend well with data for the actual occurring levels. The exhibited peaks and troughs are generally occurring at the correct time intervals. The existing discrepancies highlight the fixed nature of the empirical pan models. Over an extended period minor deviation of actual pan strikes from these models will compound and exacerbate the level differences exhibited by the stock tank predictive models as evidenced in Figure 45. Furthermore the stock tank modelling approach is dependant upon the quantification and forecast of pan drop times, fugalling delays for processing massecuite dropped to receivers and the molasses return quantities from fugalling receivers. Inaccuracies in determining return streams have a direct affect on stock tank levels and will cause stock tank level differences.

For the syrup stock tank level prediction, Section 5.2.1 details that the syrup prediction model is limited in its forecast abilities to a 96 minute window. This is the approximate time it takes for syrup from the cane crushing process to reach the pan stage. Beyond this period the average syrup rate is used. During the period in which the average syrup rate is used, if the cane crushing rate increases or decreases this will introduce syrup stock tank level discrepancies as the syrup supply will either be overstated or understated. This limitation may also have had an affect on the outcome of the syrup stock tank level prediction results, in Figure 45, during the latter intervals of the forecast.

Forecast Time	Predicted Syrup Tank Level (t)	Actual Syrup Tank Level (t)	Syrup Prediction Difference (t)	Predicted A Molasses Tank Level (t)	Actual A Molasses Tank Level (t)	A Molasses Prediction Difference (t)	Predicted B Molasses Tank Level (t)	Actual B Molasses Tank Level (t)	B Molasses Prediction Difference (t)
12:00:00 AM	96.34	135.52	39.18	79.47	76.01	-3.46	96.13	108.46	12.33
12:15:00 AM	73.47	118.14	44.67	109.53	86.63	-22.90	84.57	117.44	32.87
12:30:00 AM	73.50	98.51	25.01	135.86	110.81	-25.05	87.09	111.32	24.23
12:45:00 AM	57.63	74.86	17.23	162.22	125.46	-36.76	97.69	107.81	10.12
1:00:00 AM	48.30	56.29	7.99	168.38	139.04	-29.34	108.28	102.67	-5.61
1:15:00 AM	23.10	35.07	11.97	167.00	159.54	-7.46	115.85	97.43	-18.42
1:30:00 AM	26.98	19.56	-7.42	149.44	161.34	11.90	110.61	94.63	-15.98
1:45:00 AM	45.63	17.77	-27.86	125.83	149.93	24.10	104.89	91.13	-13.76
2:00:00 AM	66.98	31.06	-35.92	99.38	125.86	26.48	99.18	87.95	-11.23
2:15:00 AM	88.34	53.16	-35.18	72.87	100.71	27.84	93.46	81.48	-11.98
2:30:00 AM	109.69	79.20	-30.49	59.00	83.43	24.43	87.75	78.41	-9.34
2:45:00 AM	131.04	103.07	-27.97	50.77	72.13	21.36	82.03	75.18	-6.85
3:00:00 AM	152.40	124.33	-28.07	54.71	65.35	10.64	76.37	71.96	-4.41
3:15:00 AM	161.50	150.47	-11.03	60.30	90.68	30.38	85.45	65.98	-19.47
3:30:00 AM	149.53	135.95	-13.58	62.51	95.44	32.93	94.23	75.14	-19.09
3:45:00 AM	156.16	136.90	-19.26	59.53	90.92	31.39	100.21	85.75	-14.46
4:00:00 AM	148.00	159.90	11.90	67.16	100.20	33.04	110.39	91.92	-18.47
4:15:00 AM	120.69	147.53	26.84	95.65	109.75	14.10	111.92	102.01	-9.91
4:30:00 AM	126.30	130.83	4.53	126.65	123.72	-2.93	107.00	103.86	-3.14
4:45:00 AM	108.11	113.55	5.44	152.97	143.73	-9.24	110.31	97.17	-13.14
5:00:00 AM	102.95	86.23	-16.72	160.63	155.74	-4.89	121.70	90.90	-30.80
5:15:00 AM	86.04	70.24	-15.80	160.72	165.46	4.74	133.09	102.65	-30.44
5:30:00 AM	75.61	41.64	-33.97	150.13	171.50	21.37	140.19	115.90	-24.29
5:45:00 AM	90.21	27.58	-62.63	130.67	152.91	22.24	135.83	128.19	-7.64
6:00:00 AM	109.32	29.59	-79.73	111.14	127.61	16.47	130.84	129.20	-1.64
6:15:00 AM	130.67	45.82	-84.85	82.62	99.58	16.96	125.30	131.13	5.83
6:30:00 AM	152.02	66.03	-85.99	61.78	78.79	17.01	119.76	130.37	10.61
6:45:00 AM	173.38	93.42	-79.96	52.71	57.46	4.75	114.22	124.03	9.81
7:00:00 AM	194.73	122.54	-72.19	49.85	48.50	-1.35	108.69	117.35	8.66
7:15:00 AM	215.78	147.40	-68.38	54.67	49.32	-5.35	109.61	110.40	0.79
7:30:00 AM	206.09	166.60	-39.49	60.41	77.32	16.91	120.23	102.23	-18.00
7:45:00 AM	196.39	146.43	-49.96	67.17	82.33	15.16	130.84	108.82	-22.02

Table 23: Results of stock tank level prediction for the forecast time of 11:45PM 03/09/2003

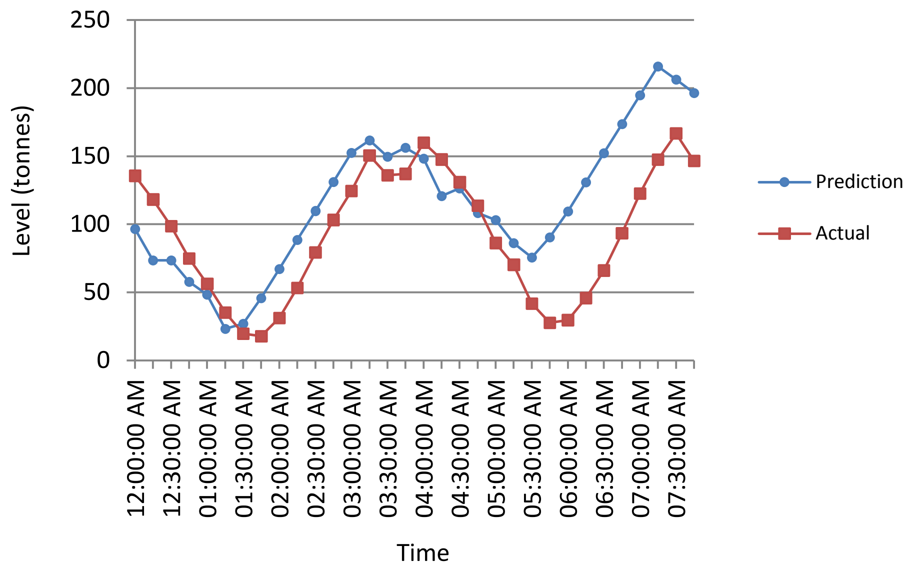

Figure 45: An eight hour forward prediction of syrup tank levels made at 11:45PM 03/09/2003

From the evaluations of the predictions of the KBSSS generated future stock tank levels, the forecast values compare favourably with the actual stock tank levels that occur. In the absence of human experts, end users using the predicted stock tank levels in conjunction

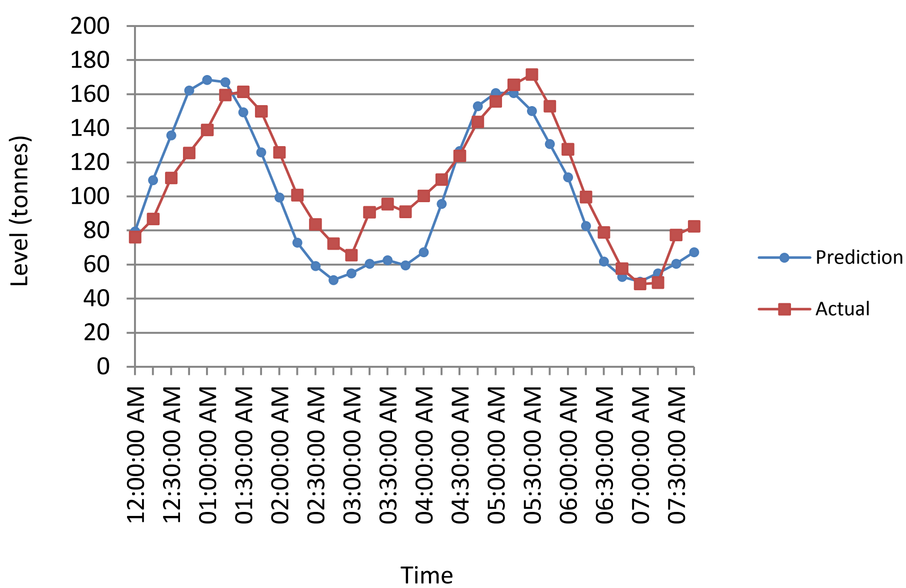

Figure 46: An eight hour forward prediction of A molasses tank levels made at 11:45PM 03/09/2003

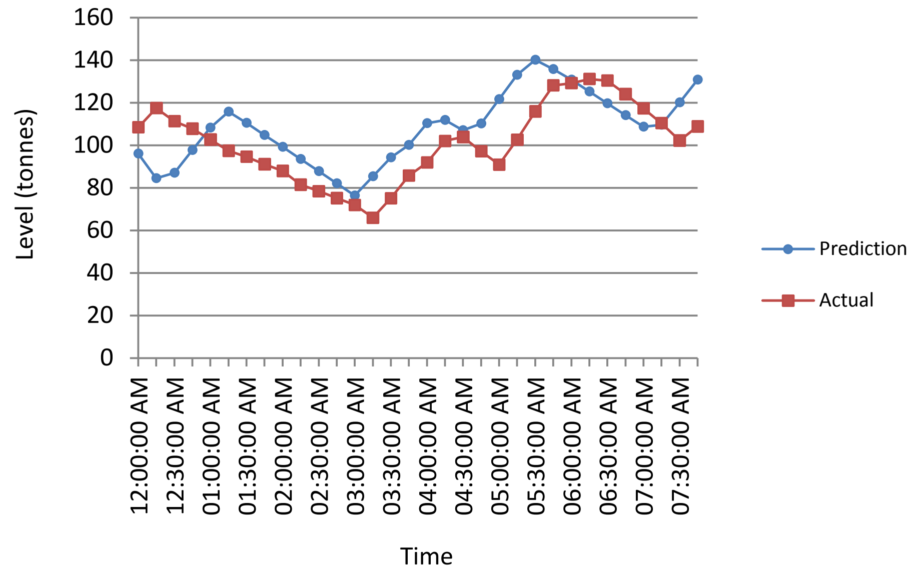

Figure 47: An eight hour forward prediction of B molasses tank levels made at 11:45PM 03/09/2003

with the strategies provided by the KBSSS, can apply the KBSSS recommendations with confidence in the KBSSS forecasting mechanics.

6.5.4 Explanatory Discourse

Explanatory discourse supporting information is based upon active If-Then rules from the fuzzy inference proces. This information provides additional support and justification of the input parameters and output data from the pan stage process models. Information from the explanatory process is referenced directly to the related pan stage process model and associated with either the pre-processing or post-processing phases of the prediction process as presented in Section 5.5.

Table 24 details results of the discourse and explanation process undertaken during the forecast process for the simulation undertaken for the time of 11:45PM 03/09/2003. Supporting information for the pan stage steady state flow model, empirical pan models and stock tank prediction models is presented. This discourse information helps to explain and justify the pre-processing and post-processing phases of the prediction.

Model	Discourse Association	Discourse Explanation
Stock Tank Level Prediction Model	Pre-processing	For Batch Vacuum Pan Number 2 dropping product massecuite to Receiver Number 1 for fugalling, the expected delay till the receiver contents are able to be processed affects the point at which molasses returns to the stock tanks will commence. The expected residence time till fugalling operations will commence for Receiver Number 1 is moderate. With Batch Vacuum Pan Number 2 designated as a swing pan the molasses return type, for fugalling of the dropped massecuite, is dependant upon its current allocated massecuite production duties.
Stock Tank Level Prediction Model	Pre-processing	For Batch Vacuum Pan Number 9 dropping product massecuite to Receiver Number 9 for fugalling, the expected delay till the receiver contents are able to be processed affects the point at which molasses returns to the stock tanks will commence. The expected residence time till fugalling operations will commence for Receiver Number 9 is moderate. With Batch Vacuum Pan Number 9 designated as a swing pan the molasses return type, for fugalling of the dropped massecuite, is dependant upon its current allocated massecuite production duties.
Stock Tank Level Prediction Model	Pre-processing	For Batch Vacuum Pan Number 3 dropping product massecuite to Receiver Number 2 for fugalling, the expected delay till the receiver contents are able to be processed affects the point at which A molasses returns to the A molasses stock tank will commence. The expected residence time till fugalling operations will commence for Receiver Number 2 is nil. Batch Vacuum Pan Number 3 is designated for A massecuite production and A molasses will be returned to the A molasses stock tank.
Stock Tank Level Prediction Model	Pre-processing	For Batch Vacuum Pan Number 4 dropping product massecuite to Receiver Number 2 for fugalling, the expected delay till the receiver contents are able to be processed affects the point at which A molasses returns to the A molasses stock tank will commence. The expected residence time till fugalling operations will commence for Receiver Number 2 is nil. Batch Vacuum Pan Number 4 is designated for A massecuite production and A molasses will be returned to the A molasses stock tank.
Stock Tank Level Prediction Model	Pre-processing	For Batch Vacuum Pan Number 6 dropping product massecuite to Receiver Number 3 for fugalling, the expected delay till the receiver contents are able to be processed affects the point at which B molasses returns to the A molasses stock tank will commence. The expected residence time till fugalling operations will commence for Receiver Number 3 is nil. Batch Vacuum Pan Number 6 is designated for B massecuite production and A molasses will be returned to the B molasses stock tank.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 1 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.

Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 2 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 3 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 4 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 5 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 6 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 7 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	Continuous Vacuum Pan Number 8 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident.
Empirical Vacuum Pan Models	Post-processing	Batch Vacuum Pan Number 9 has excellent operational performance. Operational performance affects the vacuum pans liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces are evident. The reduced boil-on rates of feed materials increases pan strike times.
Empirical Vacuum Pan Models	Post-processing	The crystallisation characteristics for syrup feed materials is excellent. Poor crystallisation characteristics when processing syrup feed materials decreases the syrup boil-on rates for vacuum pans during the processing of 'slow growth' materials.
Empirical Vacuum Pan Models	Post-processing	The crystallisation characteristics for A molasses feed materials is excellent. Poor crystallisation characteristics when processing syrup feed materials decreases the syrup boil-on rates for vacuum pans during the processing of 'slow growth' materials.
Empirical Vacuum Pan Models	Post-processing	The crystallisation characteristics for B molasses feed materials is excellent. Poor crystallisation characteristics when processing syrup feed materials decreases the syrup boil-on rates for vacuum pans during the processing of 'slow growth' materials.
Pan Stage Steady State Flow Model	Pre-processing	The fugal purity rise varies with the point in the cane crushing season. Compared to the mid-season, the fugal purity rise is higher during the early and late season. The current point in the crushing season is mid.

Table 24: Discourse supporting information for the forecast performed for 11:45PM 03/09/2003

From the results of this test it can be concluded that the KBSSS is capable of supporting discourse explanation to assist in justification of pan stage process model input parameters and output data through the reproduction of discourse information from its discourse and explanation databases. The power of the explanatory capabilities is afforded in being able to directly reproduce explanatory and discourse databases.

The explanatory and justification supporting capabilities are not complex and are only limited to the discourse information constructed by the discourse/explanation engineers for the textual based explanations. Although these explanations are relatively *simple* they suit the fundamental KBSSS requirements and the supporting information. The explanations provided are both appropriate and sufficient to assist in the justification and support of the pan stage process models prediction process.

6.6 Summary

This chapter has demonstrated the two key functional phases of the KBSSS which are: 1) knowledge acquisition; and 2) consultation process. A test of the KBSSS has been performed to evaluate system performance.

Within the knowledge acquisition section, fuzzy modelling was undertaken to provide localisation adaption of one of the pan stage process model input parameters with this knowledge gathered from research. This knowledge was then transformed into a series of fuzzy If-Then rules. The constructed fuzzy sets, predicates, rules and associated explanatory discourse were then demonstrated by saving these parameters to databases storing information on knowledge base, fuzzy If-Then rule base and the discourse/explanatory base.

This section was then followed by a consultation of the KBSSS through invoking the software application to provide pan stage recommendations for test case data. Test results demonstrate the viability of the modelling approach undertaken to relate sections of the pan stage and the feasibility of the KBSSS mechanics in providing localisation adjustments, through integration of the pan stage process models with fuzzy If-Then rules, for adaption of input/output process model parameters.

In the next chapter, a summary of the research undertaken in this thesis is presented. This is followed by a discussion of the deployment issues on how the KBSSS application can be embedded in existing infrastructure. The chapter concludes the thesis by providing areas of future research.

Chapter 7: Conclusions and Further Research

7.1 Introduction

This is the final thesis supporting chapter and provides a summary of research carried out within the thesis. Based upon the preceding chapters, this chapter provides a summary of the proposed KBSSS for improved pan stage best practices and management. This is followed by coverage of the deployment issues to allow the integration of the proposed KBSSS into existing sugar mill factory infrastructure. The chapter concludes with the presentation of areas for further research.

This chapter is structured as follows. Section 7.2 provides a summary of the research. Section 7.3 outlines deployment issues and Section 7.4 reviews areas of further research.

7.2 Summary of Research and Results

The recent downturn in world sugar prices has placed even greater demands upon the Australian sugar industry to reduce the costs of sugar manufacture and increase the consistency of producing high quality sugar. In order to take advantage of financial incentives introduced for the 2003 sugar season onwards, increase the consistency of very high quality sugar and leverage further avenues for cost saving, a smarter strategy for operations are required. As reviewed in Chapter 2, there is a need for expert advice in the area of pan stage operations however there exists a shortage of pan stage experts with constraints already existing on their time. These factors results in the recognition of a KBSSS scheme for the sugar mill pan stage environment as being beneficial in providing advice to operators in the areas of pan stage management and best practices given the absence of human experts. In Chapter 3, a KBSSS framework was proposed, to overcome the aforementioned problems, through the provision of an intelligent systems architecture specifically developed for pan stage operations within the sugar mill environment. To demonstrate the viability of the proposed KBSSS framework a specialised software application design and structure was presented in Chapter 4, in accordance with the proposed framework.

This has been accomplished though the three core innovative system technologies, presented in Chapter 5, that form the core components of the proposed KBSSS framework. These technologies are:

1) Pan stage process models for identifying dynamic interrelations between sections of pan stage operations to allow for future forecasting of pan stage operating conditions,

2) Integration techniques for merging the developed pan stage process models into the hybrid fuzzy logic expert system rule base, and

3) Explanatory capabilities for hybrid fuzzy logic based expert system advice and recommendations.

In order to forward predict future pan stage operating conditions, a sequence of pan stage process models to describe the crystallisation process was necessary. This series of models collectively works together to describe the pan stage relationship with other segments of the sugar mill, along with actual models of the internal workings of the pan stage itself. This pre-emptive approach, through the use of pan stage process models to forecast future operating conditions can aid in providing preventative measures through identifying problem scenarios before they occur.

A fuzzy If-Then rule based merger technique for the integration of process models into fuzzy rule antecedent and consequent components has been proposed. This allows the encoding of the developed pan stage process models as a major part of the system knowledge base and provides adaption of pan stage process models to suit current operating conditions. This is achieved through the inclusion of heuristic data that is not part of the predefined static knowledge base and matching against existing real world conditions for localisation adjustment.

The final technology presented was the mechanics of the explanatory capabilities employed within the KBSSS. A trace based rule tagging system was adapted and extended for use within the KBSSS to allow for justification and support of offered system advice and recommendations to end users.

In Chapter 6 the testing of all major system features was demonstrated. Pan stage control system data was used as the primary system input. Case study results were presented in this chapter with system output used to asses the performance and capabilities of the KBSSS. Results demonstrated in this thesis indicate the viability of the proposed KBSSS framework, as implemented for the specified problem, and highlight the forecasting capabilities of the developed intelligent system application resulting in favourable outcomes compared to data from pan stage operations.

7.3 Deployment Issues

The proposed implementation and deployment of the KBSSS as presented in Chapter 3 is a cooperative pan stage solution working in conjunction with existing infrastructure and pan stage operators. The developed KBSSS application cannot exist as stand alone software. The KBSSS requires information sources ranging from pan stage operators, knowledge base, fuzzy rule base and industrial process models of the pan stage to data from cane receival sections, juice processing station, the pan stage and centrifugal station sections of the sugar mill. Whilst existing sugar mill control system data is available in existing infrastructure, there is no readily available mechanism for facilitating the embedding of a secondary system such as the KBSSS.

Due to the underlying data interaction that occurs as part of the proposed KBSSS framework, the underlying rationale for deployment of the system and integration with existing infrastructure has already been committed to indirectly, although not formally specified, as part of the system framework in Chapter 3. This deployment infrastructure is not a separate system to the proposed KBSSS architecture and works in as part of the proposed system framework.

The proposed deployment infrastructure can be decomposed into the following six levels:

1. Data sources;
2. Knowledge base;
3. Industrial process models;
4. KBSSS software application;

5. System access; and
6. End users.

7.3.1 Data Sources, Knowledge Base and Industrial Process Models

The data source level consists of all information sources supplying data to the KBSSS. Local operating knowledge is elicited from end users though the consultation process and is archived for access in database format.

Sugar mill information from the cane receival, juice processing, pan stage and centrifugal sections of the factory is supplied to the data source level via parasitic data feeds from existing factory control systems infrastructure. There is no readily available solution to ensure correct information exchange between these two major systems and customisation of the underlying data sources will need to occur to ensure they mesh together correctly. In order to provide a partial solution to this problem all databases in the KBSSS have been constructed with an industry standard relational database management system running on server technology. This supplied information is used directly in the dynamic industrial pan stage models to provide a future forecast of pan stage operating conditions. The relational database management system is separate from the KBSSS client application software and database systems do not have to reside locally. These databases exist on a database server allowing dedicated computer hardware performance in the sharing of KBSSS information sources.

Industrial process models are a major feature of the knowledge base. The underlying process model algorithms are hardcoded into the overall system yet flexibility is maintained by the ease of adaptability and customisation of input and output parameters through the fuzzy logic localisation process to account for real world conditions. These features alone justify the design and development of the KBSSS. As part of factory implementation, adaption of the underlying empirical based models to suit the target implementation factory is required. Customisation of the pan stage schedule representation and steady state flow model to suit local pan stage arrangements would also be required. Since these models are specific to onsite equipment and factory performance characteristics this modelling and updating process would be performed by an expert with experience specific to pan stage operations.

The underlying KBSSS knowledge base, fuzzy If-Then rule base and explanation knowledge base consists of knowledge from experts with specialised knowledge in the area of pan stage management and best practices. They provide the practical knowledge that is captured and modelled in the KBSSS. This knowledge is stored at the KBSSS knowledge base level.

7.3.2 KBSSS Software Application

The prototype system implemented to showcase the viability of the proposed framework forms the KBSSS software application. The design, architecture and major supporting features have been extensively detailed in this thesis.

The KBSSS software application interacts directly with:

1. pan stage experts providing information at the knowledge base level;
2. pan stage operators providing information on real world conditions that are not part of the static predefined knowledge base; and
3. information sources from segments of the sugar factory through parasitic data feed from existing control system infrastructure.

The final system output is presented to pan stage operators to aid in the pan stage decision making process.

7.3.3 System Access and End Users

The deployment access level specifies how end users can access the KBSSS. The system is developed for use by pan stage operators and support staff within the sugar mill pan stage environment. For practicality, the software would run on hardware systems located in the pan stage control centre, due to the KBSSS functioning in a human cooperative support manner in the decision making process. It is important to recall that the KBSSS contains no automated feedback loop for pan stage control. Pan stage operators already have computer based access to control systems as part of their existing duties. Factory automation uses computer based control so computer infrastructure and computer networking facilities already exists as part of standard factory operations.

End users require database access permissions to KBSSS system databases. Modification of these critical database system systems without the use of KBSSS software application is not recommended. However it is technically possible with understanding of the specific information storage mechanics and familiarity with the specific software routines that collectively form the KBSSS.

Access permissions to control system data pertaining to information sources for the KBSSS are also required. Additionally such access is only to be permitted in a read-only fashion to prevent data modification of critical control system information.

7.4 Suggested Future Research

It is envisaged that the following future research avenues would continue to provide further improvements to the research undertaken as part of this thesis.

For full factory implementation further development of empirical vacuum pan models over a wider range of seasonal conditions and feed material conditions would be needed. The customisation of the empirical models used within the KBSSS would be required to suit other specific factory location for implementation. Customisation of the pan stage steady state flow model to suit local pan stage arrangements would also be required. These model updates would specifically be needed to match onsite factory equipment and factory performance characteristics.

The proposed system would require further development to handle different boiling schemes. The prototype KBSSS developed in this thesis was based upon the three massecuite boiling scheme that is common to Australian sugar mills. For system use with other boiling schemes modification to the steady state flow models and pan stage schedule representation would be required. A dynamic model loading system would also be required that would depend upon the massecuite boiling scheme used within the targeted factory for KBSSS implementation.

Further system development would be required to cover a wider range of uncommon situations such start up and shutdown periods of the cane crushing season. The developed KBSSS has been designed to operate during standard operational periods. For situations such as the start up and shutdown periods of the sugar crushing season stock tank levels will be either starting from empty levels or being run down to empty levels.

Only a prototype system was developed for the thesis supporting research in order to show the viability of the primary supporting intelligent system technologies. Further validation is required to be undertaken particularly for schedule optimisation models. Additional development of this model would include the integration with the stock tank predictive models to ensure a secondary level of checking through the provision of predictive mechanics to forecast receiver and stock tank levels. Additional research is also required for sugar crystal population balance numbers within the pan stage steady state model. As presented in Appendix C some discrepancies exist.

As a result of the research undertaken in the thesis a prototype KBSSS for pan stage operations has been developed with expectations of commercialisation for industry use upon refined development. Process models have also been developed for prediction of future pan state operating conditions with fuzzy localisation capabilities provided through adaption of input model parameters and output data. Supporting this innovation is explanatory capabilities used to provide information to support the primary KBSSS outputs.

Building upon the research presented in the thesis would be the end goal of full pan stage factory automation without the need for operators or with only minimal human operator supervision. The research contained in this thesis is a step towards this far reaching target. In achieving this goal a feedback loop and interface with pan stage control hardware would need to be undertaken given the associated adaption to the underlying KBSSS framework.

7.6 Summary

This chapter has concluded the research undertaken in the thesis. An overview of the research area and rationale for the research has been outlined. An implementation of the proposed KBSSS framework was undertaken in order to demonstrate the viability of the approach. This implementation was an intelligent system software application to provide pan stage operator support within the sugar mill environment in the provision of pan stage management and advice on best practices.

This chapter has also provided a summary of the three core intelligent system technologies supporting the KBSSS. These core technologies were pan stage process models for identifying dynamic interrelations between sections of pan stage operations to allow for future forecasting of pan stage operating conditions, integration techniques for merging the developed pan stage process models into the hybrid fuzzy logic expert system rule base and explanatory capabilities for hybrid fuzzy logic based expert system advice and recommendations. Test results demonstrated in the thesis indicate the viability of the proposed KBSSS framework and highlight the forecasting capabilities of the developed intelligent system application resulting in favourable outcomes compared to data from pan stage operations. Deployment issues were also presented on how the proposed KBSSS framework can be integrated into existing infrastructure. As a result of the research undertaken in the thesis a prototype KBSSS, for pan stage operations, based upon the three core supporting intelligent system technologies reported in the thesis has been developed.

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Appendix A – Syrup Prediction Model

The following appendix provides the data used to derive an empirical factory operational fraction. This measure is used in the prediction of syrup quantities to the pan stage. The empirical factory operational fraction determines the fractional sucrose and impurity losses through bagasse and mud by-products and consequently the sucrose and impurity quantity loadings in syrup to the pan stage for cane entering the sugar factory. This determines future syrup quantity loadings to the pan stage and allows a forward forecast of the future pan stage loading of syrup.

Syrup rates for the results presented in Table 1 and Table 2 were measured by magnetic flow meter. Cane quantities were measured at the cane receival station while pol%cane was calculated from juice laboratory analysis of the first expressed juice sample. Sucrose%syrup and dry substance%syrup values were measured in laboratory shift analyses.

Standard Week	Crushing Week	Pol % Cane	Cane Crushed (tonnes)	Dry Substance % Syrup	Sucrose % Syrup	Purity % Syrup	Liquor Produced (tonnes 92 brix)	Liqour Produced (actual tonnes)	Sucrose in Cane (tonnes)	Sucrose in Syrup (tonnes)
16	1	13.06	19155	66.79	59.19	88.62	2562.00	3529.03	2501.64	2088.83
17	2	13.19	77924	66.43	59.43	89.46	12392.00	17161.88	10278.18	10199.31
18	3	13.74	81333	67.31	60.85	90.40	13232.00	18085.63	11175.15	11005.11
19	4	14.21	82735	69.27	62.72	90.54	13635.00	18109.14	11756.64	11358.05
20	5	14.59	83637	70.14	63.44	90.45	14160.00	18573.14	12202.64	11782.80
21	6	14.65	78954	69.43	63.32	91.20	13507.00	17897.80	11566.76	11332.88
22	7	14.93	84327	69.42	62.42	89.92	14680.00	19454.91	12590.02	12143.76
23	8	15.06	83086	69.72	63.15	90.58	14653.00	19335.57	12512.75	12210.41
24	9	15.03	76645	69.15	62.61	90.54	13508.00	17971.60	11519.74	11252.02
25	10	15.25	85692	69.15	62.88	90.93	15039.00	20008.50	13068.03	12581.35
26	11	15.84	82823	69.17	62.93	90.98	15212.00	20232.82	13119.16	12732.51
27	12	16.14	78426	69.26	63.29	91.38	14641.00	19448.05	12657.96	12308.67
28	13	16.31	80746	69.11	62.76	90.81	15469.00	20592.50	13169.67	12923.86
29	14	16.59	83181	67.14	61.23	91.20	15945.00	21848.97	13799.73	13378.13
30	15	16.75	74999	67.83	61.60	90.82	14565.00	19754.98	12562.33	12169.07
31	16	16.99	79182	66.88	60.98	91.18	15455.00	21259.87	13453.02	12964.27
32	17	17.18	80974	66.92	60.89	90.99	16163.00	22220.50	13911.33	13530.06
33	18	17.36	77695	66.61	60.63	91.02	15987.00	22080.83	13487.85	13387.61
34	19	17.33	70969	69.52	62.74	90.25	14419.00	19081.53	12298.93	11971.75
35	20	17.43	75186	68.97	61.97	89.85	15305.00	20415.54	13104.92	12651.51
36	21	17.55	76946	68.26	61.53	90.14	15891.00	21417.70	13504.02	13178.31
37	22	17.28	73227	67.86	61.16	90.13	14692.00	19918.42	12653.63	12182.11
38	23	16.88	72705	69.18	61.55	88.97	14526.00	19317.61	12272.60	11889.99
39	24	16.53	79155	68.12	59.84	87.84	15574.00	21033.59	13084.32	12586.50
40	25	16.33	17564	67.45	59.49	88.20	3266.00	4454.74	2868.20	2650.12
Average		15.85	74290.64	68.36	61.70	90.26	13779.12	18528.19	11804.77	11458.36
St Dev		1.38	17262.88	1.14	1.31	0.96	3404.57	4587.12	2875.24	2852.11
Stats on weeks:		1-25	1-25	1-25	1-25	1-25	1-25	1-25	1-25	1-25

Table 1. Racecourse sugar mill 2002 crushing season empirical factory operational fraction determination

Empirical Factory Operational Fraction (Sucrose in Syrup / Sucrose in Cane)	Sucrose Prediction (tonnes)	Difference (tonnes)	Cane Impurities (%)	Impurities in Cane (tonnes)	Impurities in Syrup (tonnes)	Empirical Factory Operational Fraction (Impurities in Syrup / Impurities in Cane)	Impurity Prediction (tonnes)	Difference (tonnes)
0.8350	2443.35	-354.52	1.68	321.21	268.21	0.8350	313.73	-45.52
0.9923	10038.69	160.61	1.55	1210.62	1201.33	0.9923	1182.41	18.92
0.9848	10914.77	90.33	1.46	1186.38	1168.33	0.9848	1158.74	9.59
0.9661	11482.71	-124.66	1.48	1227.77	1186.15	0.9661	1199.17	-13.02
0.9656	11918.32	-135.52	1.54	1288.74	1244.40	0.9656	1258.71	-14.31
0.9798	11297.26	35.63	1.41	1116.12	1093.56	0.9798	1090.12	3.44
0.9646	12296.67	-152.92	1.67	1411.89	1361.84	0.9646	1378.99	-17.15
0.9758	12221.20	-10.79	1.57	1301.80	1270.35	0.9758	1271.47	-1.12
0.9768	11251.33	0.68	1.57	1203.31	1175.34	0.9768	1175.27	0.07
0.9628	12763.54	-182.20	1.52	1303.06	1254.53	0.9628	1272.70	-18.17
0.9705	12813.49	-80.97	1.57	1300.87	1262.53	0.9705	1270.56	-8.03
0.9724	12363.03	-54.35	1.52	1194.00	1161.05	0.9724	1166.18	-5.13
0.9813	12862.82	61.04	1.65	1332.50	1307.62	0.9813	1301.45	6.18
0.9694	13478.19	-100.07	1.60	1331.97	1291.27	0.9694	1300.93	-9.66
0.9687	12269.63	-100.57	1.69	1270.51	1230.73	0.9687	1240.91	-10.17
0.9637	13139.57	-175.30	1.64	1301.62	1254.33	0.9637	1271.29	-16.96
0.9726	13587.20	-57.14	1.70	1377.65	1339.90	0.9726	1345.55	-5.66
0.9926	13173.59	214.02	1.71	1330.32	1320.43	0.9926	1299.32	21.11
0.9734	12012.36	-40.61	1.87	1329.08	1293.73	0.9734	1298.12	-4.39
0.9654	12799.58	-148.06	1.97	1480.30	1429.09	0.9654	1445.81	-16.72
0.9759	13189.38	-11.07	1.92	1477.04	1441.41	0.9759	1442.62	-1.21
0.9627	12358.80	-176.69	1.89	1386.19	1334.53	0.9627	1353.89	-19.36
0.9688	11986.65	-96.67	2.09	1521.36	1473.93	0.9688	1485.92	-11.98
0.9620	12779.46	-192.96	2.29	1810.46	1741.58	0.9620	1768.28	-26.70
0.9240	2801.37	-151.25	2.19	383.78	354.60	0.9240	374.83	-20.24
0.9725	11529.72	-71.36	1.71	1255.94	1218.43	0.9725	1226.68	-8.25
0.0089	2808.24	122.77	0.23	305.08	302.28	0.0089	297.97	14.24
2-24	1-25	1-25	1-25	1-25	1-25	2-24	1-25	1-25

Table 1 (continued). Racecourse sugar mill 2002 crushing season empirical factory operational fraction determination

Standard Week	Crushing Week	Pol % Cane	Cane Crushed (tonnes)	Dry Substance % Syrup	Sucrose % Syrup	Purity % Syrup	Liquor Produced (tonnes 92 brix)	Liquor Produced (actual tonnes)	Sucrose in Cane (tonnes)	Sucrose in Syrup (tonnes)
16	1	13.80	79302	70.15	63.80	90.95	12342	16186.23	10943.68	10326.81
17	2	14.04	114609	70.50	64.50	91.49	18317	23903.04	16091.10	15417.46
18	3	14.24	109851	70.63	64.10	90.75	18567	24184.68	15642.78	15502.38
19	4	14.48	109488	70.92	64.40	90.81	18457	23943.09	15853.86	15419.35
20	5	14.64	116825	70.06	63.80	91.06	19722	25898.14	17103.18	16523.02
21	6	14.81	116220	69.71	63.70	91.38	19799	26129.79	17212.18	16644.68
22	7	15.04	113603	72.36	64.40	89.00	20633	26233.22	17085.89	16894.20
23	8	15.01	114838	70.06	64.40	91.92	19942	26187.04	17237.18	16864.45
24	9	14.88	113768	69.30	63.30	91.34	19579	25992.32	16928.68	16453.14
25	10	15.39	112993	69.38	63.20	91.09	20232	26828.25	17389.62	16955.45
26	11	15.71	115999	69.18	63.40	91.64	21674	28823.47	18223.44	18274.08
27	12	15.73	111550	69.86	63.60	91.04	20311	26747.95	17546.82	17011.70
28	13	15.93	122947	69.74	64.40	92.34	22554	29752.91	19585.46	19160.87
29	14	16.25	111825	68.32	62.40	91.33	21395	28810.60	18171.56	17977.81
30	15	16.39	103406	68.69	62.90	91.57	19501	26118.68	16948.24	16428.65
31	16	16.59	89778	68.68	62.60	91.15	17215	23060.28	14894.17	14435.74
32	17	16.87	108979	68.18	62.70	91.96	21228	28644.41	18384.76	17960.05
33	18	16.91	102101	67.98	62.00	91.20	20264	27424.07	17265.28	17002.92
34	19	16.98	114146	67.89	61.70	90.88	22620	30653.12	19381.99	18912.97
35	20	16.94	114302	67.27	60.60	90.08	22875	31284.38	19362.76	18958.33
36	21	16.97	112667	67.46	61.10	90.57	22389	30533.47	19119.59	18655.95
37	22	16.63	108492	67.48	60.40	89.51	21241	28959.28	18042.22	17491.40
38	23	16.68	118976	69.20	61.60	89.02	23696	31503.35	19845.20	19406.07
39	24	16.39	25852	69.25	60.20	86.93	0	0.00	4237.14	0.00
Average		15.72	106772	69.26	62.88	90.79	20198	26860.95	16770.70	16899.02
St Dev		1.05	19550	1.24	1.36	1.18	4726	6395.65	3255.59	3941.11
Stats on weeks:		1-25	1-25	1-25	1-25	1-25	1-25	1-25	1-25	1-25

Table 2. Marian sugar mill 2002 crushing season empirical factory operational fraction determination

Empirical Factory Operational Fraction (Sucrose in Syrup / Sucrose in Cane)	Sucrose Prediction (tonnes)	Difference (tonnes)	Cane Impurities (%)	Impurities in Cane (tonnes)	Impurities in Syrup (tonnes)	Empirical Factory Operational Fraction (Impurities in Syrup / Impurities in Cane)	Impurity Prediction (tonnes)	Difference (tonnes)
0.9436	10688.69	-361.87	1.37	1089.22	1027.83	0.9436	1063.84	-36.02
0.9581	15716.18	-298.72	1.31	1496.85	1434.18	0.9581	1461.97	-27.79
0.9910	15278.31	224.07	1.45	1593.56	1579.26	0.9910	1556.43	22.83
0.9726	15484.47	-65.12	1.47	1605.08	1561.09	0.9726	1567.68	-6.59
0.9661	16704.68	-181.66	1.44	1678.15	1621.22	0.9661	1639.05	-17.82
0.9670	16811.14	-166.46	1.40	1623.94	1570.40	0.9670	1586.11	-15.71
0.9888	16687.79	206.41	1.86	2111.86	2088.16	0.9888	2062.65	25.51
0.9784	16835.56	28.90	1.32	1514.95	1482.19	0.9784	1479.65	2.54
0.9719	16534.24	-81.10	1.41	1604.61	1559.54	0.9719	1567.23	-7.69
0.9750	16984.44	-28.99	1.50	1700.44	1657.99	0.9750	1660.82	-2.83
1.0028	17798.84	475.25	1.43	1661.38	1666.00	1.0028	1622.67	43.33
0.9695	17137.97	-126.28	1.55	1727.09	1674.42	0.9695	1686.85	-12.43
0.9783	19129.12	31.76	1.32	1624.01	1588.81	0.9783	1586.17	2.63
0.9893	17748.17	229.65	1.54	1723.97	1705.59	0.9893	1683.80	21.79
0.9693	16553.35	-124.70	1.51	1560.10	1512.27	0.9693	1523.75	-11.48
0.9692	14547.14	-111.40	1.61	1446.59	1402.06	0.9692	1412.88	-10.82
0.9769	17956.39	3.65	1.47	1606.83	1569.71	0.9769	1569.39	0.32
0.9848	16863.00	139.92	1.63	1665.26	1639.96	0.9848	1626.46	13.50
0.9758	18930.39	-17.42	1.70	1944.48	1897.43	0.9758	1899.18	-1.75
0.9791	18911.61	46.73	1.86	2131.18	2086.67	0.9791	2081.53	5.14
0.9758	18674.10	-18.15	1.77	1990.19	1941.93	0.9758	1943.82	-1.89
0.9695	17621.84	-130.43	1.95	2114.88	2050.32	0.9695	2065.61	-15.29
0.9779	19382.80	23.26	2.06	2448.43	2394.25	0.9779	2391.38	2.87
0.0000	4138.42	-4138.42	2.46	636.98	0.00	0.0000	622.14	-622.14
0.9767	16379.94	-185.05	1.60	1679.17	1683.10	0.9767	1640.04	-27.07
0.0099	3179.74	861.10	0.28	357.40	443.20	0.0099	349.07	127.96
2-24	1-25	1-25	1-25	1-25	1-25	2-24	1-25	1-25

Table 2 (continued). Marian sugar mill 2002 crushing season empirical factory operational fraction determination

The empirical factory operational fraction can be calculated using data from the mill under consideration. Using 2002 weekly crushing season data from Racecourse and Marian Sugar Mills (excluding data for the first and final weeks of the season where potential errors in stock tank levels are substantial) the relationships presented in Table 3 were derived. This summary is presented from the data provided in Table 1 and Table 2.

Sugar mill	Length of crushing season (weeks)	Average weekly empirical factory operational fraction	Seasonal standard deviation of empirical factory fraction
Racecourse	25	0.9725	0.0089
Marian	24	0.9767	0.0099

Table 12: Seasonal empirical operational coefficients for Marian and Racecourse 2002 crushing season

The empirical factory operational fractions appear to be consistent among the various weeks for a particular factory and between factories. This is evidenced by the low values of standard deviation and similar mean values. This fraction determines the quantity of sucrose and impurities from cane that reaches the pan stage after losses due to the mud and bagasse factory product stream along with the inclusion of analytical errors for measurements.

It may be considered that:

$$e = 1.0 - f \qquad (1)$$

where,

e is a fractional estimate of impurity/sucrose loss between cane receival and the pan stage (i.e. impurity/sucrose losses to mud and bagasse),

f is the empirical factory operational fraction.

Equation (1) indicates that the collective analytical errors in measurements and impurity/sucrose losses to bagasse and mud appear to be fairly consistent both within the mill crushing season and across mills.

The derived equation, to predict the future quantity of sucrose in syrup to the pan stage, is presented in Equation (2). The relationship for impurities in syrup to the pan stage is presented in Equation (3). When summated these models predict the quantity of syrup to the pan stage. This total quantity of syrup is the quantity of solids, taken as the sum of sucrose and impurities, and excludes the quantity of water that is present in practice.

$$s = fqp/100 \tag{2}$$

where,

s is quantity of sucrose in syrup to the pan stage (t)

f is an empirical factory operational fraction

q is the quantity of cane crushed (t)

p is pol%cane of crushed cane (%)

$$i = fqp(100-t)/t \tag{3}$$

where,

i is quantity of impurities in syrup to the pan stage (t)

q is the quantity of cane crushed (t)

t is purity of syrup to the pan stage (%)

The data required for the model represented by Equation (2) and Equation (3) are pol%cane, quantity of cane crushed and the purity of the syrup. The purity of syrup corresponding to the cane crushed in a shift (or shifts) will not be available until the lab analysis is performed later in the day. The previous days information on syrup purity is instead used as an approximation for the current days value.

The prediction of the quantities of sucrose and impurities in syrup from cane receival information has been decomposed to a solution of only several variables while maintaining a high overall predictive capability. The defined relationships are used to establish a link between cane receival information and sucrose and impurity quantities to the pan stage.

Appendix B – Empirical Vacuum Pan Models

Background

One approach to modeling the individual pan production rates is to set up empirical relationships for the rate at which each pan takes feed material (liquor, A molasses or B molasses) during the different phases of the pan's operation. This boil-on rate for feed materials is a function of the massecuite level and phase of the pan, steam rate, head space pressure (vacuum), brix and purity of the feed liquor/molasses.

The approach has been applied to the pan stage of Racecourse Mill. An example is given in Figure 1 for pan 3 which is a single run-up small A strike pan. The pan takes a footing of approximately 40 tonnes of high grade seed massecuite, boils on liquor initially and then A molasses to complete the A massecuite strike at a pan full level of approximately 60 tonnes. The liquor feed rate during different phases may be determined from the change in level during the run up from the footing to the end of the liquor feeding period. To determine this rate, the brix of the massecuite in the pan, the brix of the starting seed footing and the brix of the liquor feed were measured. Similarly, massecuite samples at the start and end point of the A molasses feeding phase were taken and the brix measured to determine the A molasses feed rates achieved during pan operation.

Using this method it is possible to construct a piece-wise model of pan feed rate characteristics during each phase of the pan’s operation for each of the pans detailed in Table 4. Racecourse Mill utilizes batch pans for all operations except for the C massecuite production. Thus, the model for the boil-on rate can be established for each feed material during each phase (based on massecuite level) as the pan progresses to each target level where a cut out, change in feed material or pan discharge occurs. The boil-on rate models for each pan are determined by undertaking similar measurements through the different phases of each pan’s operation. This is the modeling approach undertaken.

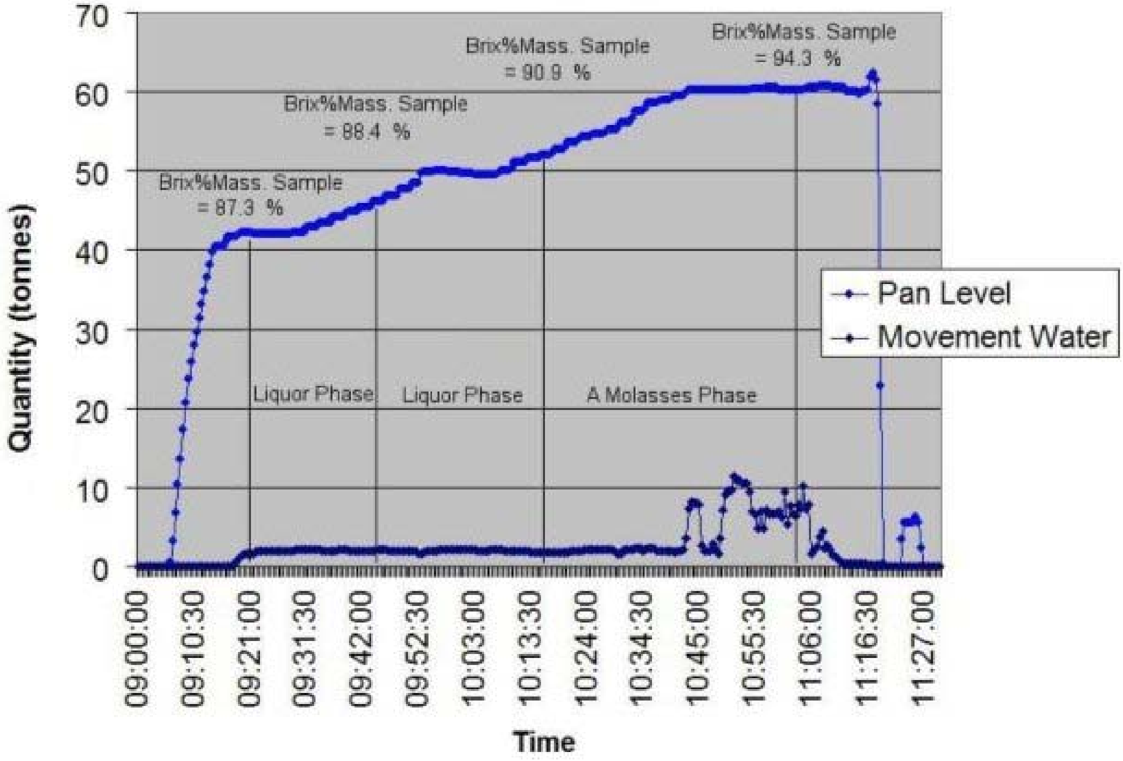

Figure 1. Data for pan 3 at Racecourse sugar mill during an operating cycle on 04/09/2003.

The boil-on rate model is a function of the following parameters: evaporation rate, vacuum, pan level and feed material purity and brix.

Pan number	Maximum pan capacity (t)	Pan duty
1	88	High grade seed
2	113	B
3	75	A
4	203	A
5	42	C seed
6	135	B
7	59	C seed
8	179	Continuous C
9	120	A

Table 4. Vacuum pan specifications for Racecourse sugar mill.

The maximum evaporation rate should also be determined for each pan for conditions of processing fresh, good quality cane. These rates could be determined by experimentation of the pan's operation or by mechanistic modeling of batch or continuous pans (Broadfoot, 1980; Wilson, Kapur, White and Lee, 1987; Beath and Miller, 2000; Schneider, 2003).

The KBSSS (Dodd, Yu, Broadfoot and Chiou, 2002) will utilize such models to recommend a steam rate to ensure that the pans 'mesh' into the target schedule and advise on the best practice of steam usage throughout a pan's strike given the current cane conditions and status of the pan stage. Reduced steam consumption of pans for a given duty, through reduced use of balancing water and idling of pans, impacts on the potential cogeneration output and production of surplus bagasse.

Methodology

Samples of massecuite from high grade pan strikes at Racecourse Mill were taken at different times on 03/09/2003 and 04/09/2003 and the solids content measured using a brix refractometer. Samples were taken from pan 1 (high grade seed); pans 3, 4 and 9 on A massecuite duty and pans 2 and 6 on B massecuite duty; pans 5, 7 and 8 on C massecuite duty.

Racecourse sugar mill control system data on pan level, stirrer load, liquor/molasses feed and valve positions, injection/movement water feed and valve positions, steam rate and valve positions were recorded.

Racecourse mill laboratory analysis data provided total solids measurements for A molasses, B molasses, liquor, A massecuite, B massecuite and C massecuite on 03/09/2003 and 04/09/2003.

Empirical models were built based on the previous discussion and analysis of the control system data.

Results

Conditions at the time of sampling were typical of mid-season operations with the exception that liquor purity was relatively low. Table 5 shows the data for pan level and massecuite brix for pans 4 and 6 while Table 6 shows the corresponding data for pans 1, 2, 3 and 9. Table 7 contains the results of the analyses from Racecourse Mill laboratory.

Pan number	Stage of pan operation	Pan level (t)	Time of sample	Measured brix of sample (%)
6	Boiling steadily and on A molasses feed	78.52	10:22	89.5
	Level at about 66%	92.87	10:49	89.6
	End of A molasses feed	128.47	12:09	94.0
	Before drop	135.02	12:44	95.0
4	On liquor feed	119.18	10:38	87.1
	Before A molasses feed	153.90	11:.03	86.7
	End of A molasses feed	185.61	11:59	90.8
	Before drop	187.21	12:17	93.8
	Once boiling	91.50	12:48	87.9
	Before cut out to pan 3	132.32	13:14	87.3
	Before cut out to pan 6	126.73	13:.53	87.1
	Before cut out to pan 3	127.11	14:27	86.4

Table 5. Refractometer brix data gathered at Racecourse sugar mill during A and B strikes on 03/09/2003.

Pan number	Stage of pan operation	Pan level (t)	Time of sample	Measured brix of sample (%)
2	Boiling steadily	60.33	9:48	90.2
	End of A molasses feed	92.39	11:11	92.5
	Before drop	100.89	11:45	94.3
3	Boiling steadily	45.49	9:43	88.4
	End of liquor feed	51.64	10:14	90.9
	Before drop	60.15	11:04	94.3
9	End of liquor feed	87.71	9:37	82.0
	End of A molasses feed	96.50	10:03	84.7
	Before drop	100.05	11:20	92.9
	Boiling steady	76.09	12:10	86.0
	Before cut	81.93	12:22	85.8
1	Before liquor feed	61.52	9:02	87.0
	Before drop	84.93	10:49	88.2
	Start liquor feed	61.71	13:07	88.1
	Level at approx 75% and at the start of the liquor feed	69.44	13:51	87.9

Table 6. Refractometer brix data gathered at Racecourse sugar mill during A and B strikes on 04/09/2003.

Factory stream	Total solids (%)	
	03/09/2003	04/09/2003
A Molasses	71.8	70.4
B Molasses	75.9	77.6
Syrup	66.1	66.4
A Massecuite	90.9	90.6
B Massecuite	92.3	91.3
C Massecuite	92.3	92.4

Table 7. Racecourse sugar mill laboratory analysis of pan stage samples on 03/09/2003 and 04/09/2003.

Tables 8 and 9 show the calculated boil-on rates, estimates of liquor and molasses feed rates, average net evaporation rates and average movement water rates for the high grade pans, based on the data in Tables 5, 6 and 7. Table 10 shows the corresponding data for the two C seed production pans (pans 5 and 7).

Pan number	Phase period	Time (minutes)	Starting level (t)	Ending level (t)	Starting brix (%)	Ending brix (%)	Liquor consumed (t/h)	A molasses consumed (t/h)	Average movement water rate (t/h)	Average net evaporation rate (t/h)	Boil on rate massecuite (t/h)
6	10.06am to 10.22am	16	68.00	78.52	87.12	89.50	62.53		6.19	0.04	39.45
	10.22am to 10.49am	27	78.52	92.87	89.50	89.62		40.04	4.38	12.54	31.89
	10.49am to 12.09pm	80	92.87	128.47	89.62	94.02		39.18	4.30	16.78	26.70
	12.09pm to 12.44pm	35	128.47	135.02	94.02	95.08			11.35		11.22
4	12.48pm to 1.14pm	26	91.50	132.32	87.98	87.38	122.48		0.00	28.28	94.20
	1.30pm to 1.53pm	23	94.48	126.73	87.38	87.12	109.80		0.00	25.67	84.13
	2.07pm to 2.27pm	20	100.86	127.11	87.12	86.48	99.99		0.00	21.24	78.75
	10.38am to 11.03am	25	119.18	153.90	87.14	86.70	107.28		0.56	24.51	83.33
	11.03am to 11.59am	56	153.90	185.61	86.70	90.80		52.32	3.41	21.75	33.98
	11.59am to 12.17pm	18	185.61	187.21	90.80	93.80			2.21		5.33

Table 8. Average pan feed consumption calculations for data gathered at Racecourse sugar mill during A and B strikes on 03/09/2003.

Pan number	Phase period	Time (minutes)	Starting level (t)	Ending level (t)	Starting brix (%)	Ending brix (%)	Liquor consumed (t/h)	A molasses consumed (t/h)	Average movement water rate (t/h)	Average net evaporation rate (t/h)	Boil on rate massecuite (t/h)
2	8.57am to 9.48am	51	45.00	60.33	87.12	90.28	27.01		0.00	0.01	27.01
	9.48am to 11.11am	83	60.33	92.39	90.28	92.56		31.84	0.00	8.67	23.17
	11.11am to 11.45am	34	92.39	100.89	92.56	94.34		24.20	8.24	17.44	24.20

3	9.14am to 9.43am	29	40.43	45.49	87.38	88.42	15.24			0.02	15.24
	9.43am to 10.14am	31	45.49	51.64	88.42	90.96		18.54	2.05	8.69	18.54
	10.14am to 11.04am	50	51.64	60.15	90.96	94.36		16.65	4.92	11.37	16.65
9	12.10pm to 12.22pm	12	76.09	81.93	86.00	85.80	36.57		0.00	0.05	36.57
	8.54am to 9.37am	43	65.52	87.71	85.80	82.00	32.98		0.00	0.01	32.98
	9.37am to 10.03am	26	87.71	96.50	82.00	84.78		32.38	0.00	12.10	32.38
	10.03am to 11.20am	77	96.50	100.05	84.78	92.90			0.74	0.00	2.76
1	9.02am to 10.49am	107	61.52	84.94	87.00	88.22	18.06				18.06
	1.07pm to 1.51pm	44	61.71	69.44	88.19	87.98	13.69				13.69

Table 9. Average pan feed consumption calculations for data gathered at Racecourse sugar mill during A and B strikes on 04/09/2003.

Pan number	Phase period	Time (minutes)	Starting level (t)	Ending level (t)	Starting brix (%)	Ending brix (%)	Molasses consumed (t/h)	Average movement water rate (t/h)	Average net evaporation rate (t/h)	Boil on rate massecuite (t/h)
5	2.49am to 3.14am	25	0.00	27.04			39 (A mol) [2]			n/a
	2.49am to 3.14am	25	0.00	27.04			21 (B mol) [2]			n/a
	4.50am to 7.00am	130	26.37	33.44	85.50[1]	87.00[1]	2.46 (B mol)	1.44	1.89	3.26
7	2.50am to 6.12am	202	44.71	57.17	87.00[1]	89.00[1]	4.69	1.36	0.00	

							(B mol)			3.70

[1] Estimate [2] Graining blend

Table 10. Average pan feed consumption calculations for data gathered at Racecourse sugar mill during low grade strikes on 03/09/2003.

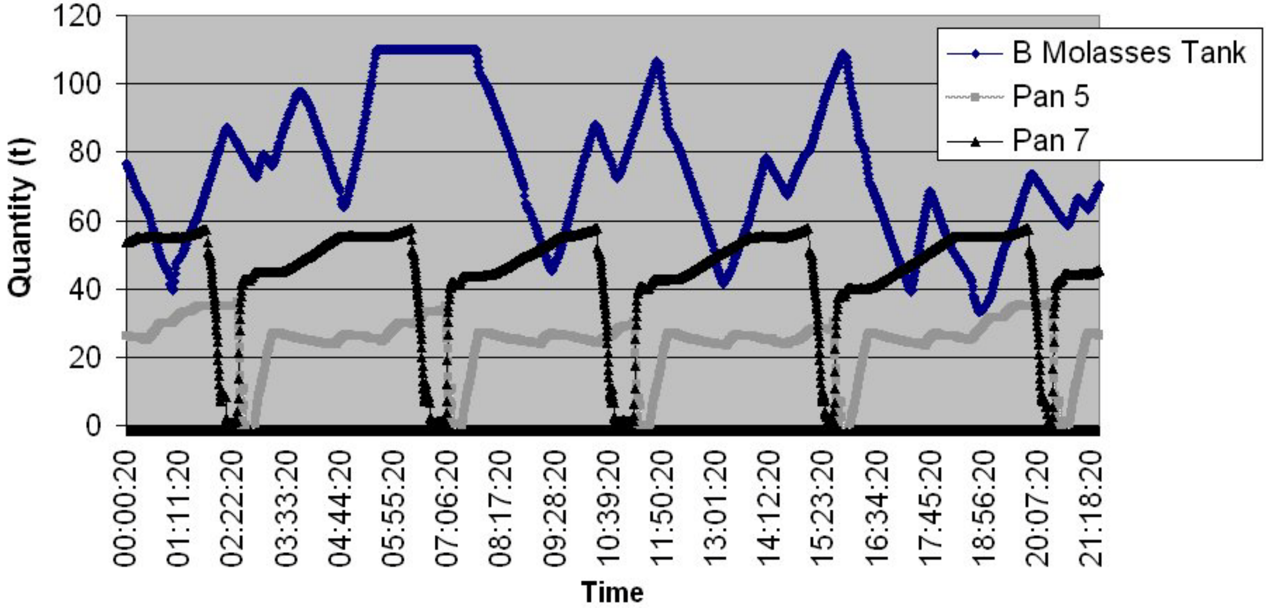

Figure 2. Operating quantities for the B molasses tank and the two batch C seed pans on 03/09/2003.

Figure 2 shows the quantity of B molasses held in the stock tanks and the quantity of massecuite in pans 5 and 7. From Figure 2 the B molasses tank level increases when the high grade fugals are processing B massecuite from pans 2 and 6. Feeding of pans 5 and 7 and number 8 continuous pan causes the B molasses tank level to decrease. The average B molasses consumption rate of the continuous C pan (pan 8) can be derived directly from information on the B molasses stock tank levels in conjunction with the average B molasses consumption rates for pan numbers 5 and 7 from Table 10. Calculations of the B molasses consumption rate for pan 8 were undertaken for three periods for the data shown in Figure 2. These data are shown in Table 11 and indicate that the B molasses consumption rate for pan 8 was relatively steady at approximately 27 t/h.

Phase period	Time (minutes)	Starting level (t)	Ending level (t)	Molasses tank feed rate (tph)	Pan 8 molasses consumption (tph)
8:19am to 9:26pm	67	86.78	47.47	35.20	28.05
12:03pm to 1.15pm	72	84.13	43.43	33.91	26.76
4:23pm to 5:19pm	56	71.19	40.04	33.39	26.24

Table 11. Pan 8 consumption rates on 03/09/2003.

Variation of Production Rate with Steam Rate

In order to determine a relationship between steam usage rates and the expected pan strike times a level based iterative computer simulation for a batch pan was developed. The model utilized a series of increments between footing level and pan full level. The feed added in each increment was determined by feedback control to the conductivity set point. At each interval the steam rate conditions were checked against the heat transfer capabilities of the pan and also that the supersaturation and crystal content of the massecuite were at appropriate levels. At the specified target level the feed material change was made. The pan simulation ended when the massecuite had undergone a simulated heavy-up and reached the target crystal content.

Simulations of strike development were carried out for the conditions shown in Table 12. These data are for the supply of liquor and molasses that would typically be processed from a fresh cane supply. The results for steam rate simulations for A, B and C strikes are given in Figures 3, 4 and 5 and show the different times taken to complete the strike due to the different boil-on rates.

Conditions	A strike	B strike	C strike
Dropping quantity (t)	200	200	200
Footing quantity (t)	66	80	66
Footing purity (%)	88	88	67
Footing dry substance (%)	87	87	87
Initial massecuite crystal content (%)	38	38	20
Liquor feed purity (%)	90	90	n/a
B molasses purity (%)	n/a	n/a	64
A molasses purity (%)	72	72	n/a
Average crystal starting size (micrometers)	550	550	150
CV of crystal distribution	0.25	0.25	0.25

Table 12. Conditions for strike simulations.

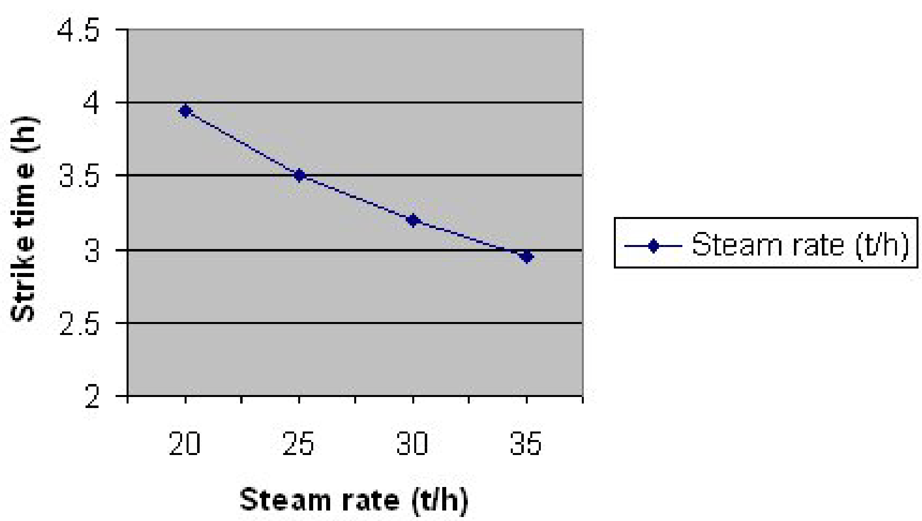

Figure 3. Simulations for A pan strikes at different steam rates.

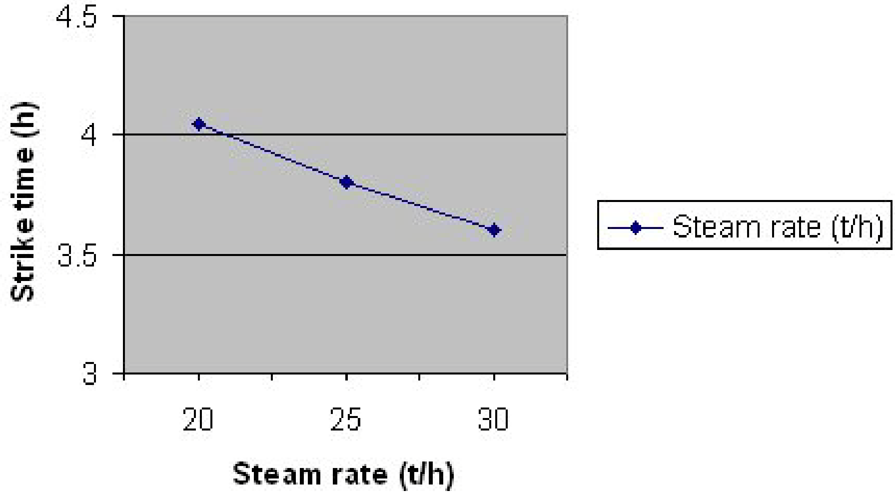

Figure 4. Simulations for B pan strikes at different steam rates

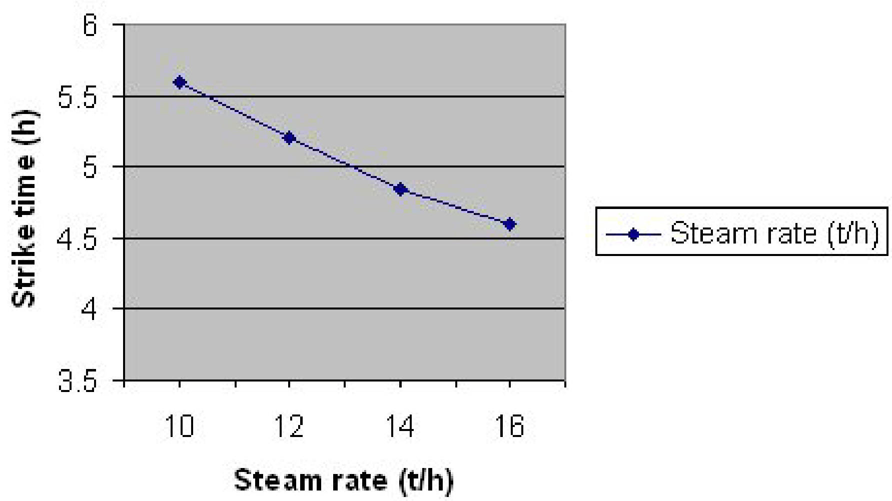

Figure 5. Simulations for C pan strikes at different steam rates

The rate of evaporation in a pan determines the rate at which sucrose in the mother molasses in the pan is made available for crystallisation. The rate of making sucrose available should match the sucrose deposition rate if the supersaturation and crystal content are to remain constant. Based on the relationships generated in Figures 3, 4 and 5 simple correlations can be developed between the average massecuite production rate and steam rate for each pan.

Miscellaneous Factors which Influence Boil-on Rates

If the crystallisation rate slows e.g. because of stale cane, the rate of steam addition must be reduced to hold the process conditions (supersaturation, crystal content as indicated through the measured value of conductivity) at pre-defined values. Hence the maximum steam rate that can be used depends on the crystallisation properties of the feed material at the time. This will be affected by the freshness of the cane supply, the purity of the feed materials and the presence of any growth rate impeding impurities.

The results of the vacuum pan simulations for each phase of the strike can be analyzed to provide correlations between the boil-on rates of the liquor and molasses streams. For the given feed material conditions in Table 12 the boil-on rates for A, B and C strike simulations are presented in Figures 6, 7 and 8.

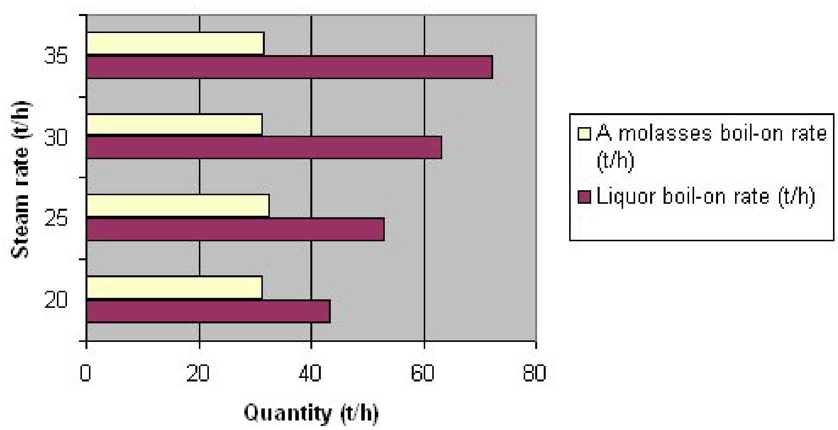

Figure. 6. Boil-on rates for A molasses and liquor feed streams for A pan strike simulations at different steam rates

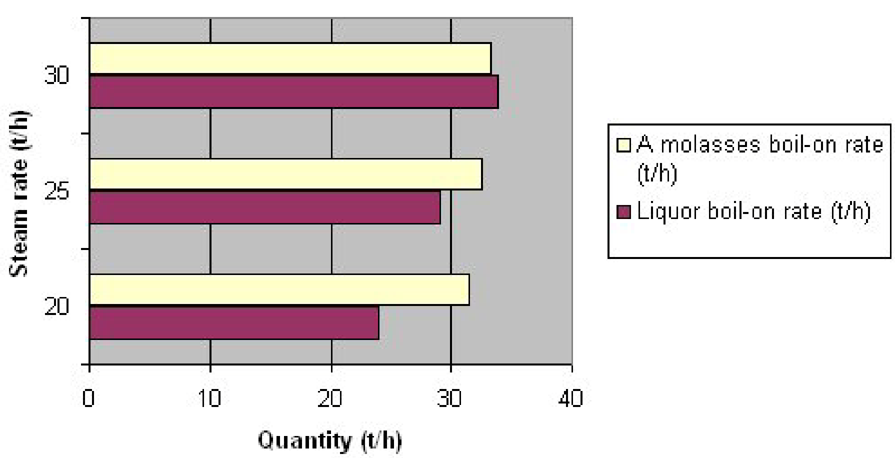

Figure 7. Boil-on rates for A molasses and liquor feed streams for B pan strike simulations at different steam rates

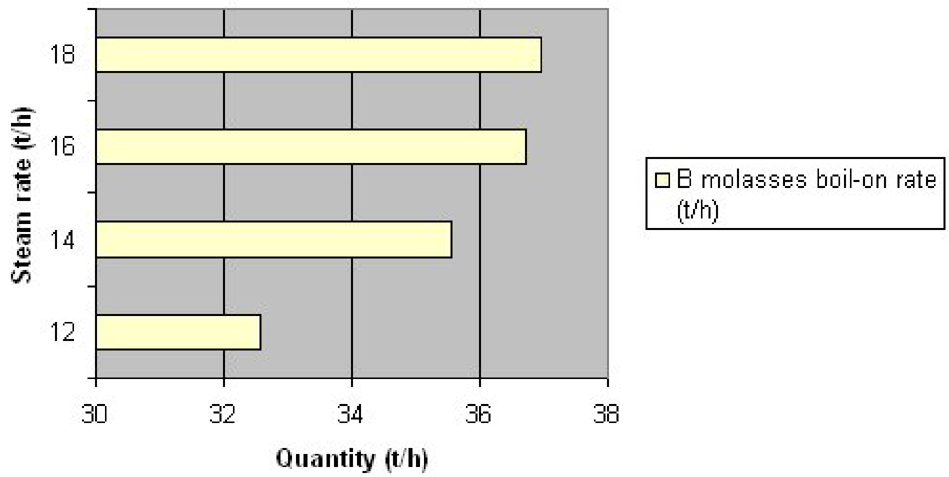

Figure 8. Boil-on rates for B molasses feed streams for C pan strike simulations at different steam rates

It is proposed to use a 'crystallisation characteristic factor' for the liquor, A molasses and B molasses streams to allow for changes in feed boil-on rates when processing 'slow growth' materials. In practice these factors would not be changed very often and would be set by the factory supervisor as appropriate, for operations over a period of several days. Separate factors would be used for these three streams to relate to the inherent differences of each stream. The 'crystallisation characteristic factor' would be defined as a fraction to set the appropriate liquor and molasses boil-on rates for each stage of a pan cycle, depending on the feed properties at the time. These factors would be set based on the experience of production staff when processing similarly affected materials.

An equipment performance factor is to be incorporated for each pan. This fractional factor would be imposed to the liquor and molasses boil-on rates if problems such as low vacuum or scaled tube surfaces have an effect on an individual pan's performance. Such operational problems would increase pan strike times and may impact on the entire pan stage schedule if the key pan(s) of the stage are affected. This factor is to be brought into the decision making process for pan stage schedule synchronization.

Summary

Once the model for each pan is established then the boil-on rates for each feed stream at the different stages of the pan stage schedule can be determined by summing the liquor, A molasses and B molasses feed rates for all the pans at that point in the schedule. Given the expected liquor production rate, C sugar remelt production rate and raw wash return from the refinery to the liquor tank during this interval, the predicted tank levels can be determined for the liquor tank. Similarly the predicted tank levels for the A and B molasses streams can be calculated from the production rates and the molasses at the centrifugal station and the sum of the consumption rates on the individual pans at a specific point in the pan stage schedule.

A steam profile for A, B and C massecuite duties has been developed to assist in relating strike time to steam consumption of the vacuum pans. Given the expected schedule and operating status of vacuum pans the strike times of pans within the schedule can be adjusted to avoid idling time and better improve productivity on rate limiting pans.

The developed models will form a core component of the KBSSS, allowing a forward prediction of stock tank levels at a future point in the pan stage schedule and assisting in forewarning of problems with the current operating strategies. Early decisions, such as changes to steam rates, or allocation of pans to different duties (e.g. A or B massecuite) can then be made to avoid production rate difficulties, and maintain good operational performance with respect to sugar quality, sugar recovery and minimization of steam consumption on the total pan stage.

Appendix C – Pan Stage Steady State Flow Model Validation

In order to validate the functionality of the proposed steady state flow model algorithm, presented in Section 5.2.2, and demonstrate its viability the model is compared to previous research (Broadfoot and Pennisi, 2001) which is used as a reference model for comparative measure. The steady state flow model is run with the parameters presented in Section 6.3.1 and an input syrup solids rate of 17.59 t/h and purity value of 92.5%.

Due to the large volume of model data results generated, a streamlined representation of the key process material solids flows and their associated purities is presented in Fig. 1. In this reduced representation certain equipment items and their associated flows have been clustered together for a compact results display.

Model solids flow rates are presented in Table 1 and purities are presented in Table 2 and compared to the reference model with relative difference calculations highlighting the

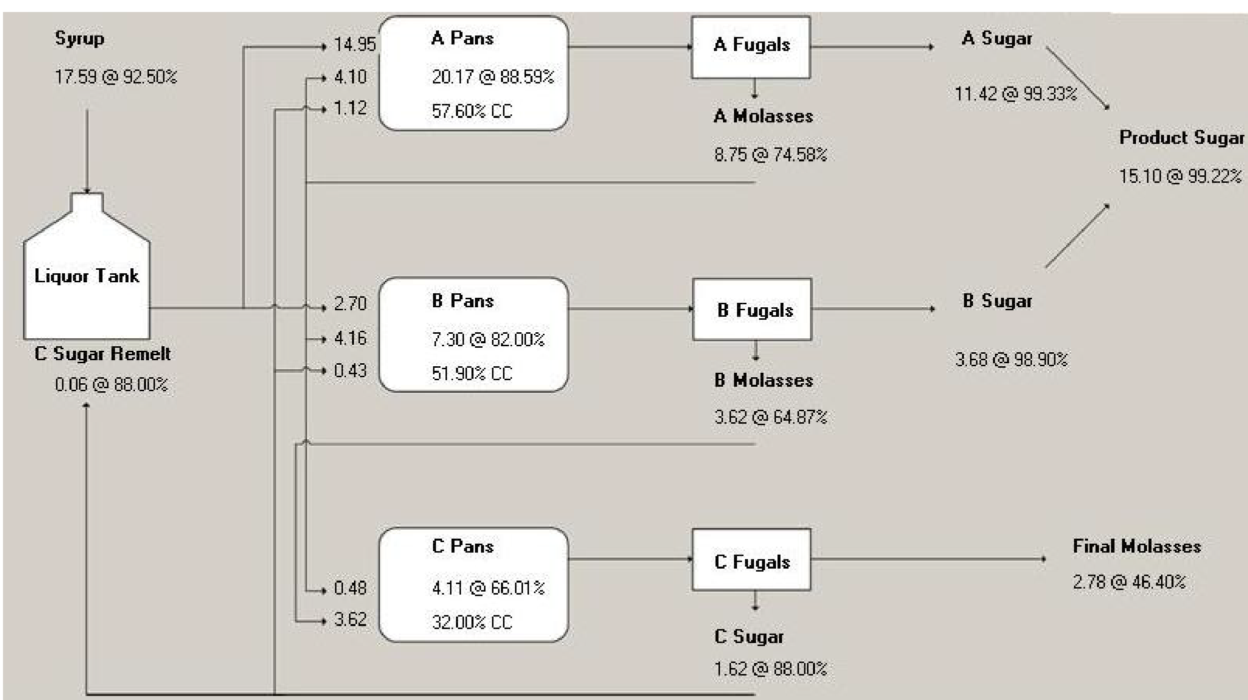

Figure 1. Solids flow results from pan stage steady state flow model.

variations between results.

The majority of solids flows presented in Table 1 closely match production quantities for the reference model. The major differences between the two approaches exist for the C sugar footing quantities for the seed pans. The cause of the difference is attributed to the population balance calculation, which needs to be investigated further. As a result solids flows for the C sugar quantities from the C fugals to the seed pans differ from their counterparts in the reference model.

The purities presented in Table 2 match reference model results very closely with an extremely low relative difference. This close matching of purity values is to be expected within the model. Once the target purities for the seed pans are correctly reached within the model, through the optimization of the fractional values for feed materials to the equipment items, consistent purity values in the remainder of the model should follow.

Flow from	Flow to	Solids flow (t/h)	Reference model solids flow (t/h)	Absolute difference to reference model (%)
Liquor Tank	A Pans	14.95	15.70	4.78
Liquor Tank	B Pans	2.70	2.90	6.90
A Fugals	A Pans	4.10	4.10	0.00
A Fugals	B Pans	4.16	4.30	3.26
A Fugals	C Pans	0.48	0.50	4.00
B Fugals	C Pans	3.62	3.80	4.74
C Fugals	A Pans	1.12	0.60	86.67
C Fugals	B Pans	0.43	0.30	43.33
A Fugals	A Sugar	11.42	11.60	1.55
B Fugals	B Sugar	3.68	3.80	3.16
A/B Sugar	Product Sugar	15.10	15.30	1.31
C Fugals	Final Molasses	2.78	2.30	20.87
A Pans	A Fugals	20.17	20.40	1.13
B Pans	B Fugals	7.30	7.50	2.67
C Pans	C Fugals	4.11	4.20	2.14

Table 1. Steady state flow model flows compared to reference model.

Flow from	Purity (%)	Reference model purity (%)	Absolute difference to reference model (%)
Liquor Tank	92.48	92.20	0.30
A Pans	88.59	88.59	0.00
B Pans	82.00	82.00	0.00
C Pans	66.01	66.09	0.12
A Fugals	74.58	74.60	0.03
B Fugals	64.87	65.00	0.20
C Fugals	88.00	88.00	0.00
A Sugar	99.33	99.33	0.00
B Sugar	98.90	98.90	0.00
Product Sugar	99.22	99.22	0.00
Final Molasses	46.40	46.80	0.85

Table 2. Steady state flow model flow purities compared to reference model.

Appendix D – Racecourse Sugar Mill Control System Data Sources

Data from Racecourse sugar mill control system sources Citect control system was extracted via the *Plant2Business* interface. This sourced information is from the cane receival, juice processing, pan stage and centrifugal station sections of the factory. The data presented is for the period up until 03/09/2003 11:45PM when the forward forecast of future operating conditions was made by the KBSSS in Section 6.5 of the thesis.

An explanation of each of the individual data types used for this information is beyond the scope of the thesis, however the information source requirements for the pan stage process models have been discussed in Section 5.2. The tables are headed with column names of the control system tags used to identify information sources within the Racecourse sugar mill control system. For system interoperability with the underlying data sources these have been preserved.

The information sources have been extracted and made available in Microsoft Access database format on DVD in the back section of the thesis. This information consists of the following four tables:

- **Tanks.** Tank levels for factory stock tanks and receivers.
- **CaneReceival.** Collated information from the cane receival and juice processing sections of the factory. All cane payment information and identifying information has been removed from this data in order to protect the privacy of the producing cane farmer.
- **PanData.** Batch vacuum pan data on tank levels, stirrer load, movement water, injection water and steam process variables, set point and control output information.
- **ContinuousPanData.** Steam usage process variables and set point information on the cells comprising the continuous pans.

These information sources are stored against time/date occurrences. For the vacuum pan and tank level data this information was captured on a 30 second interval basis. Cane receival information is collected for each rake of cane entering the factory and collated with juice processing information from the first expressed juice sample taken.

The **Tanks** table has a level for the stock tanks and receivers at each time interval. Cane data in each rake of the **CaneReceival** table has associated analysis information from the cane weighing and juice processing sections of the factory. Familiarisation with cane rake analysis measures specific to the sugar industry is required for interpretation of this data.

For the **PanData** table the following Racecourse sugar mill control system tags assist in understanding the information sets:

		Pan							
Measure	**Units**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**9**
Level	t	R_BO848	R_PO591	R_PO641	R_PO691	R_PO741	R_PO791	R_PO841	R_P1041
Stirrer Load	Amps		R_PO565				R_PO765	R_PO815	
Feed CV Output	%	R_BO847_CO	R_PO594_CO	R_PO644_CO	R_PO694_CO	R_PO744_CO	R_PO794_CO	R_PO844_CO	R_P1044_CO
Feed CV PV	mS	R_BO847_PV	R_PO594_PV	R_PO644_PV	R_PO694_PV	R_PO744_PV	R_PO794_PV	R_PO844_PV	R_P1044_PV
Feed CV SP	mS	R_BO847_SP	R_PO594_SP	R_PO644_SP	R_PO694_SP	R_PO744_SP	R_PO794_SP	R_PO844_SP	R_P1044_SP
IW CV Output	%	R_BO841_CO	R_PO596_CO	R_PO648_CO	R_PO696_CO	R_PO746_CO	R_PO796_CO	R_PO846_CO	R_P1046_CO
IW CV PV	kPa	R_BO841_PV	R_PO596_PV	R_PO648_PV	R_PO696_PV	R_PO746_PV	R_PO796_PV	R_PO846_PV	R_P1046_PV
IW CV SP	kPa	R_BO841_SP	R_PO596_SP	R_PO648_SP	R_PO696_SP	R_PO746_SP	R_PO796_SP	R_PO846_SP	R_P1046_SP
MW CV Output	%	R_BO844_CO	R_PO598_CO	R_PO646_CO	R_PO698_CO	R_PO748_CO	R_PO798_CO	R_PO848_CO	R_P1048_CO
MW CV PV	tph	R_BO844_PV	R_PO598_PV	R_PO646_PV	R_PO698_PV	R_PO748_PV	R_PO798_PV	R_PO848_PV	R_P1048_PV
MW CV SP	tph	R_BO844_SP	R_PO598_SP	R_PO646_SP	R_PO698_SP	R_PO748_SP	R_PO798_SP	R_PO848_SP	R_P1048_SP
Steam CV Output	%	R_BO843_CO	R_PO600_CO	R_PO650_CO	R_PO700_CO	R_PO750_CO	R_PO800_CO	R_PO850_CO	R_P1050_CO
Steam CV PV	tph	R_BO843_PV	R_PO600_PV	R_PO650_PV	R_PO700_PV	R_PO750_PV	R_PO800_PV	R_PO850_PV	R_P1050_PV
Steam CV SP	tph	R_BO843_SP	R_PO600_SP	R_PO650_SP	R_PO700_SP	R_PO750_SP	R_PO800_SP	R_PO850_SP	R_P1050_SP

Table 1. Vacuum pan control system tags used by Racecourse sugar mill.

For the **ContinuousPanData** table the following Racecourse sugar mill control system tags assist in understanding the information sets for continuous vacuum pan number 8:

	Control Output	Process Variable	Set Point
B Mol Heater	R_P0851_CO	R_P0851_PV	R_P0851_SP
B Mol Dilution	R_P0854_CO	R_P0854_PV	R_P0854_SP
C Seed Pump Load		R_P0860	
C Seed / B Mol Ratio	R_P0860E_CO	R_P0860E_PV	R_P0860E_SP
IW CV	R_P0886_CO	R_P0886_PV	R_P0886_SP
Cell 1 - Steam Flow	R_P0889_CO	R_P0889_PV	R_P0889_SP
Cell 2 - Steam Flow	R_P0891_CO	R_P0891_PV	R_P0891_SP
Cell 3 - Steam Flow	R_P0893_CO	R_P0893_PV	R_P0893_SP
Cell 4 - Steam Flow	R_P0895_CO	R_P0895_PV	R_P0895_SP
Feeder 1 - Water Flow		R_P0902	
Feeder 1 - Water CV	R_P0903_CO	R_P0903_PV	R_P0903_SP
Feeder 1 - Feed CV	R_P0905_CO	R_P0905_PV	R_P0905_SP
Feeder 2 - Water Flow		R_P0909	
Feeder 2 - Water CV	R_P0910_CO	R_P0910_PV	R_P0910_SP
Feeder 2 - Feed CV	R_P0912_CO	R_P0912_PV	R_P0912_SP
Feeder 3 - Water Flow		R_P0917	
Feeder 3 - Water CV	R_P0918_CO	R_P0918_PV	R_P0918_SP
Feeder 3 - Feed CV	R_P0920_CO	R_P0920_PV	R_P0920_SP
Feeder 4 - Water Flow		R_P0924	
Feeder 4 - Water CV	R_P0925_CO	R_P0925_PV	R_P0925_SP
Feeder 4 - Feed CV	R_P0927_CO	R_P0927_PV	R_P0927_SP
Feeder 5 - Water Flow		R_P0931	
Feeder 5 - Water CV	R_P0932_CO	R_P0932_PV	R_P0932_SP
Feeder 5 - Feed CV	R_P0934_CO	R_P0934_PV	R_P0934_SP
Feeder 6 - Water Flow		R_P0951	
Feeder 6 - Water CV	R_P0952_CO	R_P0952_PV	R_P0952_SP
Feeder 7 - Water Flow		R_P0954	
Feeder 7 - Water CV	R_P0953_CO	R_P0953_PV	R_P0953_SP
Feeder 6 & 7 - Feed CV	R_P0956_CO	R_P0956_PV	R_P0956_SP
Feeder 8 - Water Flow		R_P0961	
Feeder 8 - Water CV	R_P0962_CO	R_P0962_PV	R_P0962_SP
Cells 6,7 & 8 - Steam Flow	R_P0966_CO	R_P0966_PV	R_P0966_SP
Cell 6 Stirrer		R_P0980_AMPS	R_P0980_SET
Cell 7 Stirrer		R_P0981_AMPS	R_P0981_SET
Cell 8 Stirrer		R_P0982_AMPS	R_P0982_SET

Table 2. Continuous vacuum pan number 8 control system tags used by Racecourse sugar mill.