Dynamic Allocation of Predicted Quantities to Forecast Intervals for Pan Stage Supervisory Support System Process Models

R. Dodd[1], R. Broadfoot[2], A. Chiou[3] and X. Yu[1]
[1]School of Electrical and Computer Engineering, RMIT University, Melbourne, Victoria, Australia.
Email: roland.dodd@student.rmit.edu.au, x.yu@rmit.edu.au
[2]Queensland University of Technology, Brisbane, Australia.
Email: r.broadfoot@qut.edu.au
[3]School of Computing Sciences, Central Queensland University, Rockhampton, Queensland, Australia.
Email: a.chiou@cqu.edu.au

***Abstract* - This paper describes a critical feature for the industrial process models of an expert advisory system and their integration within a knowledge based supervisory support system (KBSSS) for advice on best practices and management of a sugar mill crystallization stage. This functionality works cooperatively to translate pan stage industrial process models, used during the forward prediction of pan stage operating conditions, to a time scale basis by dynamically allocating forecast processing quantities to predefined intervals over the prediction horizon. The innovative dynamic allocation procedure outlined underpins the prediction ability of the process models, acting in a backbone capacity, to establish forecasting capabilities for the system.**

The primary topic of this paper will be a description of the approach and how it supports the predictive modelling with focus on: (1) design features, (2) implementation and (3) application to the prediction of syrup quantities to the pan stage from cane receival and juice processing information.

I. INTRODUCTION

Raw sugar production from cane is a nominally continuous operation, with 120-168 hours of processing per week, extending over 20-25 weeks of the harvest season. The crystallisation section, often loosely referred to as the pan stage, is the most complex part of the factory process where there are several batch wise and continuous crystallisation steps taking place concurrently [1].

In current Australian practice, two operators are normally employed on the pan stage and usually their duties extend no 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 very large number of process streams of varying compositions and crystal growth rate characteristics which must be managed [2]. Often the pan stage is managed in a sub-optimal manner because an overview of operations encompassing various sections - cane receival section, juice processing stations, the pan stage and centrifugal station - is not available.

The pressures on the Australian sugar industry to reduce the costs of sugar manufacture and increase the consistency of producing sugar of high quality require a smarter strategy for operation.

Previous literature [3] acknowledges that no conventional software engineering methods exist to provide an overall solution to this industrial problem due to its complexity, the wide variety of information sources required to be managed, overall management objectives, lack of adequate sugar mill crystallisation stage industrial 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 solution.

Currently, there is no such supervisory control system for pan stage operations neither in the Australian sugar industry nor, as best as known to the collaborators, in the world sugar industry. The knowledge based supervisory support system uses advanced intelligent technologies to provide a standardised 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 [4].

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 pan stage inputs and outputs are required along with actual models of the internal workings of the pan stage itself. In determining pan stage inputs, this equates to establishing relationships for juice processing and how this section interacts with the pan stage. Syrup output from the juice processing section of the factory forms the primary input to the pan stage. For the purposes of providing a forward prediction and a view

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of sugar factory sectional operations, such models logically need to have a time scale basis.

An overall encompassing view of the various section of the factory is currently not available and hence operators are not able to predict future pan stage loadings with any form of assistance from existing factory systems. Furthermore, prediction facilities are not available to determine the consequence of operators actions other than the actual forward estimates the operators intuitively carry out. The technique described in this paper is an approach to help solve this problem and make such facilities available.

This paper is organised as follows. Section II discusses an overview of the sugar factory processes undertaken to produce syrup for the pan stage. Section III presents the basic KBSSS framework used and how industrial process models such as that used to predict sucrose and impurity quantities to the pan stage are integrated. Section IV discusses the major features and development of dynamically allocating quantities to future forecast intervals using the syrup quantity prediction as the basis for discussion. Section V presents results for the approach with Section VI then presenting a discussion and conclusions.

II. Syrup Production

The standard operation of a sugar factory involves the processing of large quantity of cane for the purpose of sugar production. An overview [5] of the process from cane receival to the production of syrup providing the primary input to the pan stage is now presented.

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 fed 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 cane grower depending upon the juice characteristics. Pairs of rollers feed the cane through a series of mills. 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. However, factories are now moving towards 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 still 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 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 returned to the cane fields for use as fertilizer.

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”. This product forms the primary input to the pan stage for use within the sugar crystallization process.

III. Overview of the Framework

The KBSSS is essentially a hybrid fuzzy logic based expert system incorporating fuzzy logic, explanatory capabilities and industrial process models of the pan stage. The knowledge base is composed of human operator knowledge coupled with dynamic industrial process models describing the crystallization process. The integration of such features leads to a challenge in the design and development of the KBSSS.

The KBSSSs modular architecture is based upon conventional expert systems [6,7] and conventional If-Then fuzzy rule based systems design [8,9]. Fig. 1 provides a representation of the overall system framework [4].

A core feature of this system is a predictive mechanism to determine future pan stage operating conditions with industrial process models describing the pan stage and its interaction

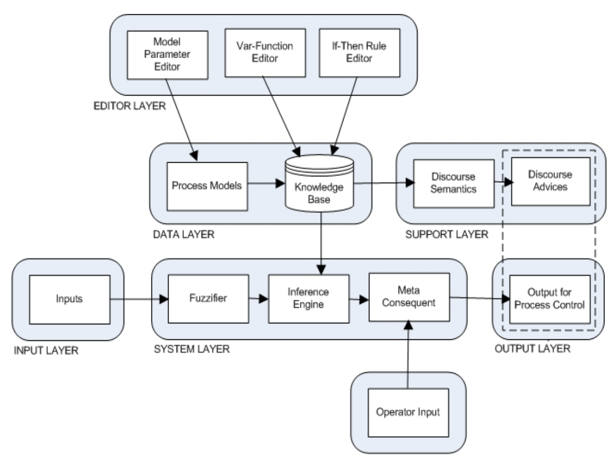

Fig. 1. Smart supervisory control system framework diagram.

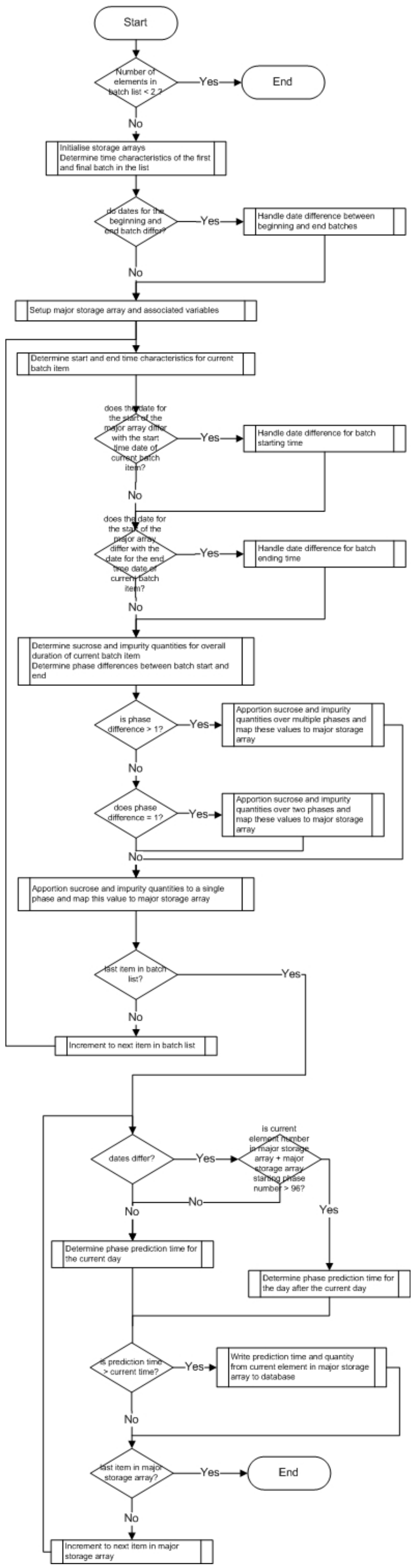

Fig. 2. Dynamic allocation algorithm used to allocate predicted quantities to future forecast intervals.

with the other sections of the sugar factory.

The intermittent nature of stock tank level fluctuations within the pan stage means an advisory scheme warning of future levels and advising on corrective strategies to current stock usage is recognized as being of beneficial use to pan stage operators and supervisors in management and best practices for pan stage operations [3,10,11].

The prediction of syrup quantities to the pan stage liquor tank determines the majority of future liquor tanks inputs with the only other feed material input consisting of a continuous remelt material stream from C sugar production. Such prediction of liquor tank levels, through the prediction of syrup quantities, will aid in the stock tank management goals which form part of the primary system control strategies and offer support in the prediction of future pan stage operating conditions [4].

This predictive behaviour is a key characteristic of dynamic process models of the pan stage expert system framework [4]. These pan stage process models are tightly integrated into and work in tandem with the expert system rule base and are a core system technology.

IV. Provision of Forecast Facilities For Syrup Prediction: Features and Development

This syrup prediction model, as established in previous literature [12], 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 a specialized dynamic forecasting algorithm was developed. 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 needs to determine and apportion the sucrose and impurity quantities for each batch to each associated prediction interval 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.

The overall algorithm as depicted in Fig. 2 consists of two major event loops. The first event loop progressively moves through each batch in a list and determines to which 15 minute interval 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 [12]. This is linearly apportioned to each phase dependant upon how many minutes of the overall duration occur within each phase. The difference in 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 Fig. 3.

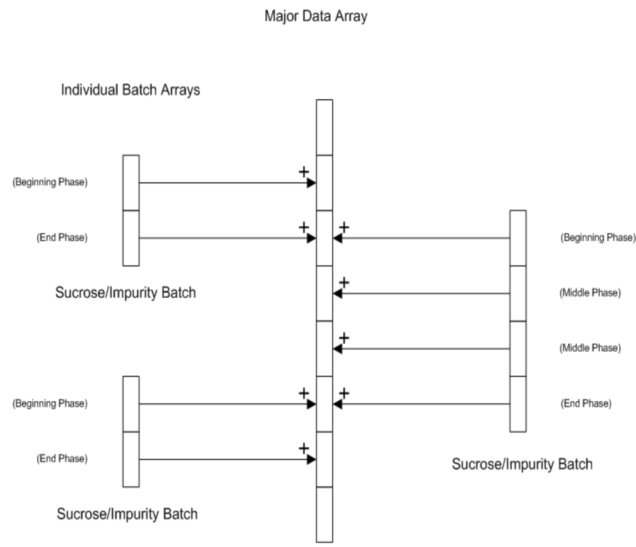

Fig. 3. Updating of major data array with quantities from individual batch array phases corresponding to the processing of sucrose/impurity batches.

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 done for allocation of syrup quantities with prediction intervals that cross the midnight threshold into a new day period.

Fig. 3 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.

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

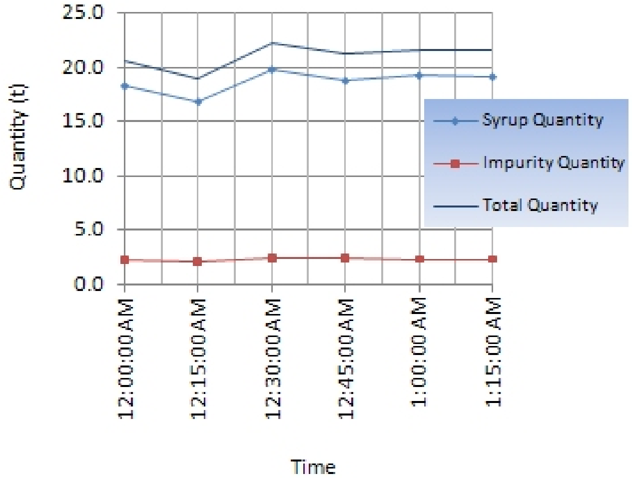

Fig. 4. Sucrose and impurity quantity forward prediction made at 03/09/2003 11:45PM.

then written to a database for further use in liquor stock tank models.

V. Results

A 90 minute forward forecast of sucrose and impurity quantities is presented in Fig. 4 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.

For the rake data presented in Table I 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 03/09/2008 and determined to be 89%. The empirical operational factory fraction used was established in previous research [12] and set as 0.9725.

Table I shows the rake data for the preceding 96 minute period before the time that the prediction is carried out. All identifying information has been removed from rake data in order to protect the data privacy of cane suppliers. A 96 minute time frame is used as this is the approximate time it takes syrup from crushed cane to reach the pan stage.

TABLE I
Cane Rake Data for the 96 Minute Period Before 03/09/2003 11:45PM

Logical Rake Number	Nett Weight (t)	Crushing Time	Pol % Cane
1	49.49	3/09/2003 22:05	15.9
2	126.06	3/09/2003 22:12	15.2
3	79.85	3/09/2003 22:27	15.1
4	102.48	3/09/2003 22:38	16.1
5	132.50	3/09/2003 22:50	15.6
6	77.17	3/09/2003 23:06	14.7
7	5.98	3/09/2003 23:15	14.1
8	36.40	3/09/2003 23:16	14.4
9	142.55	3/09/2003 23:19	14.5
10	33.01	3/09/2003 23:36	15.2

TABLE II
Breakdown of Sucrose Quantities Using Forecast Algorithm

	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	1:00AM	1:15AM
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

Using the algorithm presented in Fig. 2 sucrose and impurity quantities are allocated to the intervals shown in Tables II and III 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 specified Table I.

The total sucrose and impurity quantities from tables II and III are presented in Fig. 4 along with their associated future prediction intervals. When summated these quantities indicate the expected syrup quantity to the pan stage after cane crushing. This quantity is also presented in Fig. 4. Note: 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.

VI. Discussion and Conclusions

The syrup production rate is very consistent at approximately 25 tons of syrup quantity being delivered to the pan stage at each 15 minute interval.

The cane to syrup relationship is used to illustrate the overall method of dynamically allocating forecast quantities to future

TABLE III
Breakdown of Impurity Quantities Using Forecast Algorithm

	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	1:00AM	1:15AM
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

forecast intervals however this approach (with associated changes to the determination of prediction quantities and handling of possible process delays) is very similar. Other implementations however are complicated due to requirements for the interaction of additional industrial process models of the pan stage.

Since this 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.
- 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 very 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.

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. Often the pan stage is managed in a sub-optimal manner because an overview of operations encompassing various sections - cane receival sections, juice processing stations, the pan stage and centrifugal station - is not available. The method presented in this paper when working in tandem with the syrup prediction model allows an overview of syrup loadings to the pan stage by relating the cane receival and juice processing sections of the factory directly to the pan stage.

A time based methodology is employed for mapping forecast production quantities and apportioning them to future time intervals. It provides 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.

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