

CONTROL AND OPTIMIZATION OF A MULTIPLE EFFECT EVAPORATOR

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Abstract

Multiple effect evaporator control is a problem that has been widely reported in the pulp and sugar industries. Evaporators are the largest heat users and major contributors to losses in sugar cane factories. These factors make effective evaporator control crucial to overall factory efficiency. The complexity and large number of interactions make single loop PID control (the conventional proportional, integral and derivative control) difficult and often sub-optimal. A Model Predictive Control (MPC) algorithm is presented as a different approach to solving the multiple input, multiple output problem. This technique has been applied successfully in other multiple station industries and is being applied to a dynamic model of the evaporator station at Triangle Limited.

The first step in the MPC formulation was to develop a dynamic computer model of the quintuple effect evaporator station at Triangle. The model was then used to obtain a convolution model (the internal reference model for the controller), which captures the step response behaviour of the process to key inputs. The two inputs available for control were the juice flowrate and the steam pressure in the calandria of vessel three. Valve dynamics for these two inputs were first identified using real plant data, and the model was suitably modified so that the control system could assume linearity of these control actions. An objective function was then formulated, combining tight Brix control with a smooth overall operation. The proposed controller will use the convolution model to determine the optimal sequence of input moves.

Introduction

Multiple effect evaporators concentrate juice from the extraction plant to syrup of about 67° Brix, which is fed to the pan station (evaporative crystallisers). This involves removing the majority of the water from the juice, and thus is the unit operation that consumes the most energy in the factory. Long residence times and high temperatures create a potential loss of between 1% and 2% of incoming sugar by inversion. Therefore evaporation is a very important unit operation and must be controlled smoothly. However, the complexity of the system, and the large number of interactions, make single loop PID control difficult.

The two most commonly cited objectives for an evaporator control system are tight control of Brix, and a smooth operation. These can be made clearer by using an economic analysis. The economic objective is the delivery of the maximum amount of high quality product to the downstream factory. In the sugar factory, this quality is determined by the syrup concentration. The amount of syrup that can be delivered is constrained by the

rate at which juice arrives at the station, and there is also an upper limit on the syrup concentration in order to avoid spontaneous nucleation or excessive deposition and scaling.

Smooth operation means the even handling of extreme operating conditions, such as fluctuations in juice flowrate. Smoothing out process fluctuations, most notably the clear juice flowrate, greatly increases the potential for good evaporator control. At Triangle, two evaporator trains exist in parallel, and these are cleaned on a rotational basis. Thus the performance of the different trains is seldom identical and a higher quality product may be achieved by carefully choosing the proportion of juice that is fed to each train.

Evaporator control

Montocchio and Scott (1985) reported good results using a variation on a PID based throughput control scheme, which was installed at Amatikulu Sugar Mill. By changing the configuration of the evaporator effects, and using good variable pairings, the evaporator system was made less sensitive to disturbances. This robustness was dependent on tight juice flow control, and a well designed station, which was nearly always run at full throughput. This scenario cannot be assured in plants where flow delays due to lack of cane are common.

Hsiao and Chen (1995) also reported promising results using an improved PID model. Their algorithm includes a form of gap action control whereby the simple PID output is modified in the face of excessive variations or unusual operating conditions. The control of syrup Brix was improved by allowing a variable recycle back to the last effect. As with the throughput control used at Amatikulu, this system would limit the capacity of the station, and would not be able to anticipate and handle input constraints.

The scheme proposed by Rousset *et al.* (1989a, b) was based on a series of Feedforward/Feedback controllers. The results from this system were very promising, although a high degree of instrumentation was required on the plant. Lee and Newell (1989) proposed Generic Model Control as a means of controlling a single effect recirculation evaporator. The study was confined to simulation studies, and although the control system gave impressive results, constraints could not be handled directly, nor anticipated (Harris and McLellan, 1990).

Elhaq *et al.* (1999) have applied a multivariable Generalised Predictive Control system based on Mohtadi *et al.* (1987), to an evaporator station in Morocco. The objective function was based on the total operating cost. The two outputs chosen were syrup Brix and V2 steam pressure, which was maintained at a set value despite variations in vapour draw. Once again, this system was not able to handle input constraints directly.

In this paper, Model Predictive Control (MPC) will be introduced as a novel control algorithm, which is suitable for evaporator control, as well as other factory areas, in that it can anticipate and handle constraints, and handle Multiple Input, Multiple Output (MIMO) systems in an optimal manner. The problem under consideration can be split into three main areas – juice flow control, Brix control and juice distribution to the three first effects.

Juice Flow Control

Juice flow control is a useful introduction to the concepts of Model Predictive Control, because of the familiarity of this system. At Triangle, manipulating the mixed juice flowrate controls the clear juice tank level, while the clear juice flowrates are controlled according to operator supplied set points only. These clear juice flowrates then indirectly affect the mixed juice tank level. The algorithm presented below could be applied to both the mixed juice and clear juice tanks.

MPC controller

Campo and Morari (1989) have used a standard flow control objective, that is to minimise the Maximum Rate of Change of Outlet flow (MRCO) of the tank under consideration, with constraints that the level should not violate upper or lower bounds over some prediction horizon. These authors successfully applied a MPC algorithm to this problem. In this, a simple internal model predicts the future behaviour of the tank based on the past two level measurements, and the previous outlet flow, as outlined in the level equation (1), below:

$$h_{\text{predict}}(t+k) = h(t) + k \left[(h(t) - h(t-1)) + \frac{\Delta t}{A} Q_o(t-1) \right] - \frac{\Delta t}{A} \cdot \sum_{i=0}^k [Q_o(t+k)] \quad (1)$$

- Where h_{predict} = predicted tank level
- Δt = time-step used
- Q_o = outlet flowrates
- A = cross sectional area of tank
- t = time of last measurement
- k = time steps until prediction

Future inlet flowrates are assumed constant and are inferred by using measurements of the outlet flowrate and the change in tank levels since the previous time-step. The future outlet flowrates are chosen so as to minimise the MRCO objective,

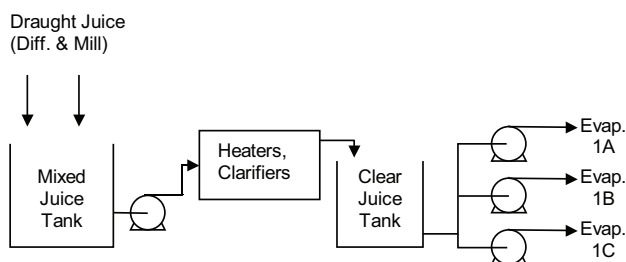


FIGURE 1. Juice Handling at Triangle Limited.

$f(Q_o(t+k))$, while obeying constraints on the permissible tank levels and flowrates. In addition, a final constraint is added, that the level must return to set point by the end of the prediction horizon (P). The control algorithm was formulated as shown below in equations (2) – (6), for any present time, t .

$$\min_{Q_o(t+k)} f = \max |Q_o(t+k) - Q_o(t+k-1)| \quad (2)$$

For $P \geq k > 0$, subject to:

$$Q_o(t+k) \leq Q_{o,\text{max}} \quad (3)$$

$$Q_o(t+k) \geq Q_{o,\text{min}} \quad (4)$$

$$h_{\text{min}} \leq h(t+k) \leq h_{\text{max}} \quad (5)$$

$$h(t+p) = h_{sp} \quad (6)$$

Only the first computed flowrate is implemented, and the optimisation is repeated at the beginning of the next time-step.

Results

This MPC controller has been programmed in the Matlab simulation language, and applied to the problem of controlling the mixed juice tank level, and the mixed juice flowrate. The following graph, Figure 2, shows the results of this system under a real life situation on the Triangle plant; i.e. a step increase in draught juice (DJ) flowrate.

The MPC controller of Campo and Morari, (1989), was formulated so that there is no offset after the prediction horizon. This is the tuning parameter in this case, and it can be shown that for any given disturbance, there is a critical prediction horizon, i.e. the time at which the tank would overflow, with no controller action. As the prediction horizon is increased, the MRCO objective is continually improved until this critical horizon is reached. Thereafter, the settling time is only increased, with no further benefit to flow filtering.

In this example, the prediction horizon was chosen as 10 minutes, which resulted in a settling time of 51 minutes, with an MRCO of 35.7, and a maximum flowrate of 866.3 tph. With a smaller prediction horizon, of 5 minutes, the settling time could be reduced to 26 minutes, at the expense of a higher MRCO, of 78.4 and a slightly higher maximum flowrate, 867.9 tph.

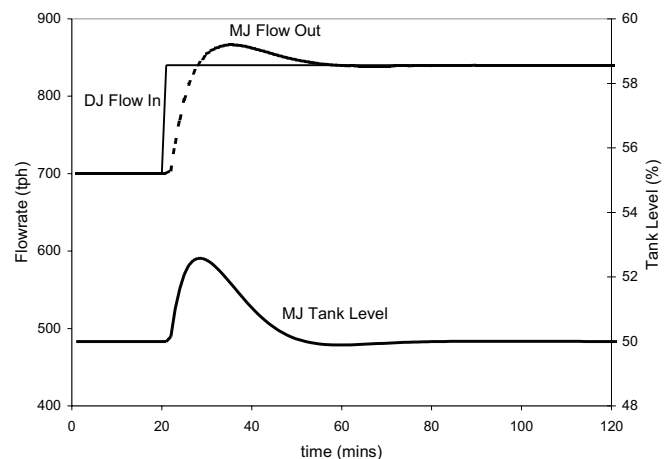


FIGURE 2. MPC response to a step in flowrate.

Model Predictive Control

Model Predictive Control refers to a group of algorithms in which an internal model is used by the controller to predict how past and present measurements will affect the real plant. From this model the optimal sequence of control moves is then computed. The first of these is then implemented, and a new set of measurements is taken at the beginning of the next time step, providing a feedback mechanism for the controller.

The future sequence of control moves is calculated by optimising an objective function, commonly a weighted sum of squares of the setpoint tracking error and the manipulated variable moves. A common formulation of this type is Dynamic Matrix Control, or DMC, which was first developed by Cutler and Ramaker (1979) at Shell Oil for tackling the multivariable control problems such as that shown in Figure 3 below.

In Dynamic Matrix Control, the model of the plant is a convolution model, i.e., the response of each output to a step change in each input is found. The values of the response at discrete sampling times then make up a series of step response coefficients (a_i) which may be used to predict the change in any output (y) associated with a change in any input (u), as shown in the general output prediction equations (7) and (8), below:

$$y_{predict}(k) = \sum_{i=1}^{n-1} a_i \Delta u(k-i) + a_n u(k-n) + d_p(k) \quad (7)$$

Where n = the settling time of the system (number of intervals)

a_i = the step response coefficients

$d_p(k)$ = predicted disturbance, which is assumed constant and is calculated by equation (8), which calculates the difference between the current measured output, and the output as predicted by the past control moves:

$$d_p(k+j) = d_p(k) = y_{measured}(k) - \sum_{i=1}^{n-1} a_i \Delta u(k-i) - a_n u(k-n) \quad (8)$$

The optimisation problem at each time-step is then to minimise the objective function, $f(Du)$, shown in equation (9), below:

$$\min_{\Delta u} f = (y_{set} - y)^T \cdot Q \cdot (y_{set} - y) + \Delta u^T \cdot R \cdot \Delta u \quad (9)$$

Where y = the vector of predicted outputs, $y_{predict}(k)$

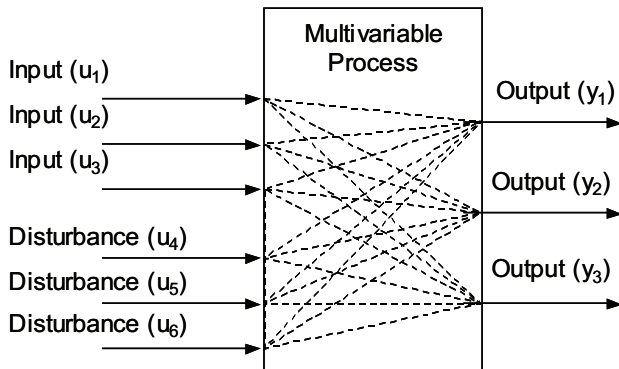


FIGURE 3. Input-Output process description used in industrial MPC technology (Qin and Badgwell, 1997).

Du = the vector of input moves $Du(k)$

Q and R are diagonal weighting matrices, and T is the vector transpose operator.

Equation (9) is a weighted sum of the predicted setpoint tracking errors for both outputs and the input variable moves for the inputs, over the prediction horizon. The optimisation must be solved subject to constraints on the inputs, outputs and input moves. This approach has been used in the Brix control section discussed below. In summary, the Model Predictive Control structure can be considered as an observer, and an optimiser, as shown in Figure 4 below. The observer receives measurements of inputs to the plant (u) and outputs from the plant (y), and by using an internal model, estimates the present and future state of the plant (x). Based on this prediction, the optimiser then determines the sequence of manipulated inputs that would best achieve the desired reference objective.

Model Predictive Brix Control

The concept of Model Predictive Control is extended here to Brix control, where the advantages of this form of control are clearer. Currently, the syrup Brix leaving the Triangle evaporator station is controlled by manipulating the flowrate of heating vapour to the third effect of each train. In Triangle this vapour is vapour two; the vapour evolved from the second effect evaporators (V2). The layout of the Triangle evaporator station is shown in Figure 5 below.

Although this control system involves only two outputs, syrup Brix and clear juice flowrate, it is still essential that this control layer should be able to anticipate and handle constraints. At Triangle Ltd. the InTouch Scanning, Control And Data Acquisition (SCADA) system has recently been installed, which provides online readings of the most significant three disturbances, i.e. juice flowrate, exhaust steam pressure and final effect pressure. The effects of these inputs are more easily included in the DMC formulation, rather than as a series of trims and feed forward gains, which would be necessary for PI control. It is for these reasons that a DMC controller has been selected.

Dynamic model

A dynamic model first had to be developed which would form the basis for the internal model of the controller. The model was based on the familiar mass and energy balances about each effect. These were solved numerically using the Runge

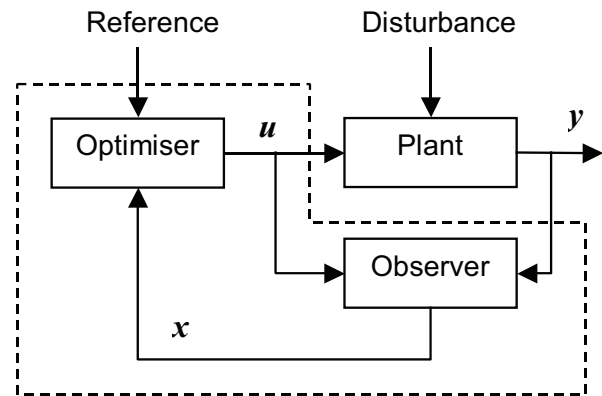


FIGURE 4. Model Predictive Controller.

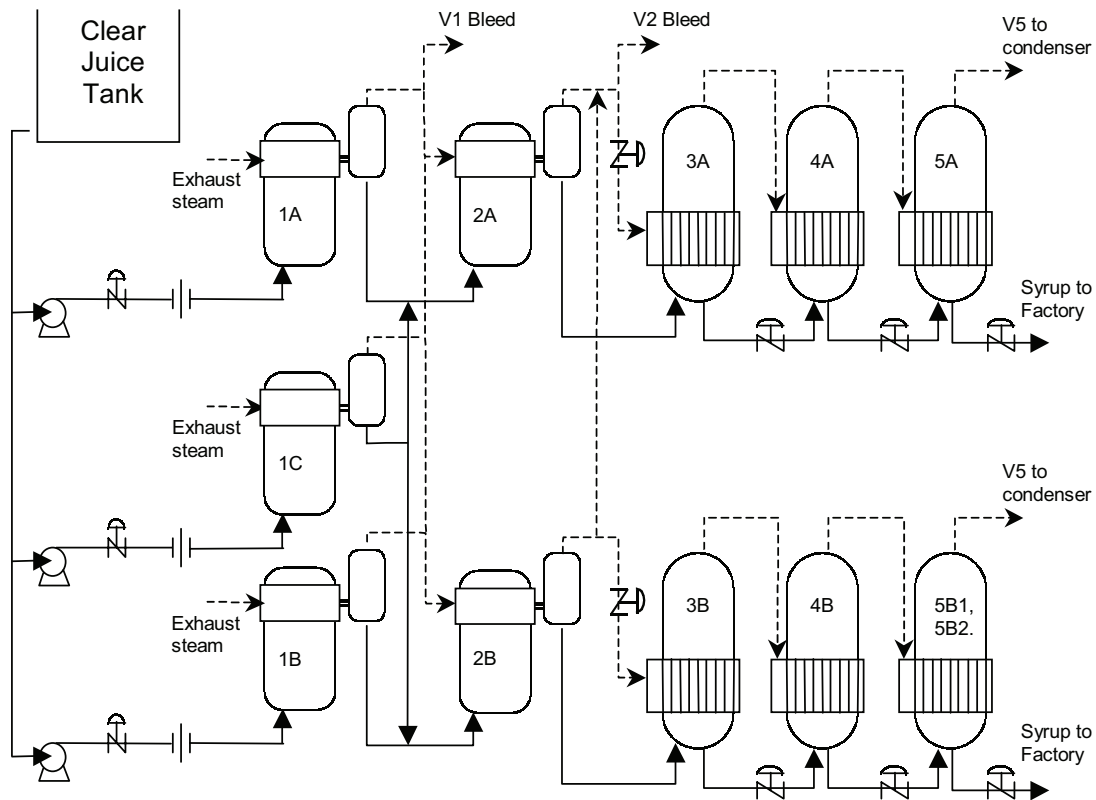


FIGURE 5. Layout of the Triangle Evaporator Station.

Kutta 4th order technique. Several other script files contain code for estimating physical properties (Peacock, 1995), calculating vessel parameters, and converting steam properties (Perry *et al.*, 1997). The existing model makes the assumption of constant liquid volume hold-up for the first two effects (without level control) while the levels in the final three effects are modelled dynamically using the existing PID controller settings.

The inputs to the model are the incoming juice temperature, concentration, and flowrate, the exhaust steam temperature and pressure, and the absolute pressure (vacuum) maintained in the final effect. These inputs were simulated using SCADA system data from the plant. The model then outputs all of the states of the system, i.e. the juice temperatures and concentrations leaving each of the 12 vessels, along with the pressures of V1 (first effect vapour) and V2 vapour for comparison with real plant data.

Steady state heat transfer coefficients for each vessel in the Triangle station had been calculated based on SCADA measurements and laboratory analyses, and these were generalised by using the Dittus - Boelter equation to take into account variations of flow and temperature from steady state, as shown in equation (10).

$$\frac{U}{U_0} = \frac{N_{Re}^{0.8} \cdot N_{Pr}^{0.4}}{N_{Re,0}^{0.8} \cdot N_{Pr,0}^{0.4}} \quad (10)$$

Where U = Heat Transfer Coefficient

N_{Re} = Reynolds number

N_{Pr} = Prandtl number

The sinusoidal dynamics of the V2 throttling valve were identified using SCADA data, and incorporated into the model. Figure 6 shows the results obtained when the model was supplied input data from the SCADA, and compared with actual data supplied by the Triangle laboratory.

Convolution model and Dynamic Matrix Controller

When the dynamic model had been completed, the response of the system was then measured for 10% steps in each of the input variables. A sampling time of 1 minute was used, as this is the smallest time interval possible from the SCADA system, and it has proven adequate for obtaining all of the process dynamics from this system. The overall juice residence time in the multiple effect is about 45 minutes, and thus the settling time to steady state was set at two hours. The convolution model is made up of the step response coefficients, i.e. the change in syrup Brix from steady state at each time interval

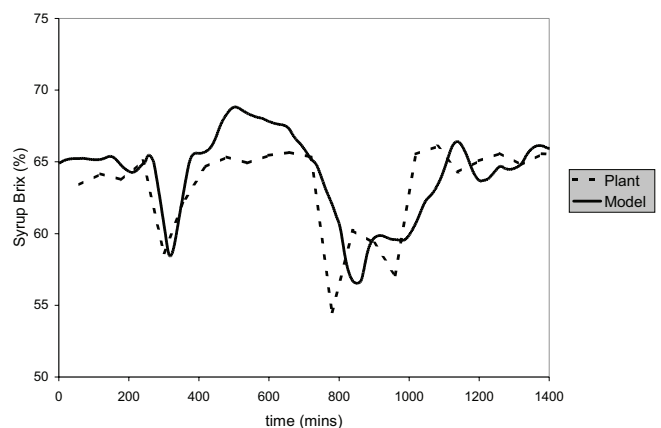


FIGURE 6. Comparison of dynamic model with plant.

following the step change. By combining the responses to steps in each of these inputs, and assuming linearity and time invariance, a Dynamic Matrix is formed, which predicts the future output of the system based on present and past inputs.

In the Triangle case there are a total of 5 inputs to the system, which give rise to two outputs, syrup Brix and actual clear juice flowrate. A clear distinction has been made between genuine adjustable input variables (A, B), and disturbance variables (c, d, e), which cannot be freely manipulated by the control system:

- A Clear juice flowrate – this can be directly manipulated via the SCADA system. In a sense, this variable is both an input and an output in the MPC formulation, in that it is available for manipulation, and a bias value is also specified as the clear juice flow setpoint.
- B V2 Valve throttling position – this can be directly manipulated via the SCADA system.
- c Clear juice temperature – any variation in this parameter must be due to random process disturbances.
- d Exhaust steam pressure – this is difficult to vary due to the arrangement with the turbo-generators, and was treated as a disturbance.
- e Final effect pressure – this is also controlled about a constant setpoint, and so any fluctuations could be counted as a disturbance.

Results

The controller was then coded into the Matlab simulation language, Simulink, and used to control the existing dynamic model of the station. Figure 7 shows the response to an increase in steam pressure at time (t = 20 mins) and again at time (t = 60 mins).

Figure 7 shows several important features of dynamic matrix control. Firstly, when the steam pressure was increased by 10% at time 20, the V2 throttling valve started to close, to counteract the effect of this increased pressure (and thus temperature) on the syrup Brix. The syrup Brix gradually returned towards a setpoint of 68°Bx from time 40 to time 60. Then, at time 60, the exhaust steam pressure was again increased by 10%. This had a similar effect, in that the syrup Brix began to

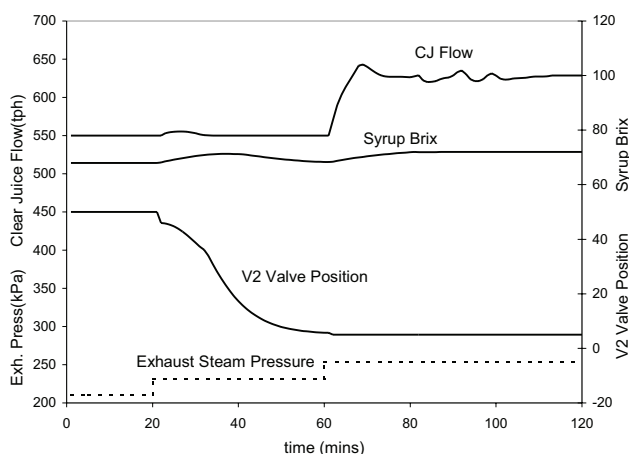


FIGURE 7. Response to steps in steam pressure.

rise. The V2 throttling valve was already almost fully closed, and now encountered an input constraint.

In the overall plant constraints, it is intended to keep syrup Brix between 50° and 72°Bx. Thus when this Brix constraint was approached, the controller increased the clear juice flowrate, the only remaining input variable move, in order to bring the syrup Brix back under control. A similar effect was observed for the case where the disturbance caused a decrease in syrup Brix, e.g. a decrease in juice temperature. In this case, the V2 throttling valve was opened until it encountered a constraint (100% open) and then the clear juice flowrate was reduced, to prevent the syrup Brix from falling below its constraint of 50°Bx.

Optimal Juice Distribution

Steady state optimisation

The final layer of the evaporator control strategy is a distribution controller. At Triangle there are three first effect evaporators, and the total clear juice flowrate must be distributed amongst these so as to achieve the highest possible syrup Brix. Because the evaporators are cleaned on a rotation basis, they may be operating at different efficiencies at any one time, and the aim of a particular flow distribution should be to optimise their current operational condition.

Determination of evaporator condition from condensate flowmeters

The distribution controller needs to receive some measure of the condition of the evaporators before optimisation can be done. This can be achieved by measuring the flowrate of condensate leaving each evaporator.

However, condensate flow measurement provides particular difficulties because the fluid being measured is at its saturation temperature. Love (personal communication), proposed that a particular design of linear weir, (Heller, 1980), would effectively address the limitations of conventional flow measurement techniques. The condensate flowmeter, as shown in Figure 8, was designed, built and tested on the Triangle station.

The flowmeter was designed so that there is a linear relationship between flowrate and head maintained in the outer cylinder.

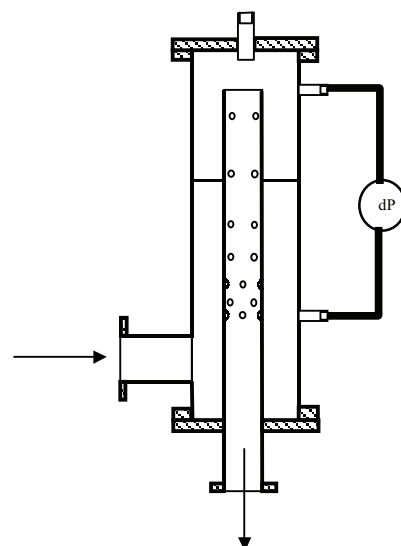


FIGURE 8. Condensate flowmeter (after Heller, 1980).

der. The vent was connected back to the incondensable gas release, to avoid flashing. A Kalman filter was then used in simulations to identify heat transfer coefficients from flowmeters fitted to each of the first and second effects, a total of five vessels (1A, 1B, 1C, 2A and 2B). The heat transfer coefficients were then used in the optimisation program, where the objective was to maximise the amount of water evaporated from the juice. This is done by calculating the weighted Brix of the juice that would leave the second effects, using part of the dynamic evaporator model described above.

Results

Figure 9 shows the optimal juice flowrate through the first vessel of the A set, as the observed heat transfer coefficient for either vessel 1A or 2A was varied. In each case, all other heat transfer coefficients were kept constant.

Figure 9 shows that the heat transfer coefficient of the first effect is more important than that of the second effect, due to the layout of the Triangle evaporator station, where there is an additional first effect vessel, which feeds the two evaporator trains equally. The responses of each of the first effect vessels were not identical.

The extra first effect, 1C, was found to have a slightly different relationship between its observed heat transfer coefficient and the optimal flow distribution.

Conclusion

The subject of evaporator control has been investigated and some recent developments have been presented. Three levels of control are proposed: juice flow control, syrup Brix control, and the optimal distribution of juice to the three first effects. Good juice flow control is crucial not only to improved evaporator control, but also to good clarification and pH control. A novel algorithm has been presented, and its advantages have been discussed briefly. Syrup Brix is significantly affected by a number of factors, and these are efficiently incorporated into an MPC framework. This type of control also allows input and output constraints to be accommodated. Finally, there is an optimal distribution of clear juice to the first effect vessels, which may be determined by their observed heat transfer coefficients.

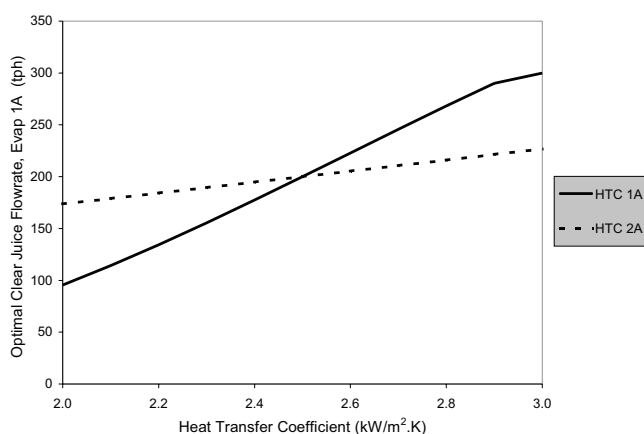


FIGURE 9. Optimal juice flowrate into vessel 1A.

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