

# **Model Based Control of Fractionation in an Ethylene Plant**

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## **Model Based Control of Fractionation in an Ethylene Plant**

The paper addresses common problems of controlling distillation, particularly superfractionators. It presents use of rigorous-model-based control (RMBC) to improve operation of such columns.

To tie the theoretical arguments with real world problems we show one example of how this control concept is carried out on a C2 splitter.

### **Effects of Control on Profitability**

Good control of fractionation has profound impact on profitability of ethylene plants. It affects product purities, plant capacities, re-circulation of olefins into cracking furnaces, energy consumption, plant stability, equipment reliability, in short good fractionation control can make the difference between mediocre and excellent plant performance.

For example figure 1 shows the influence of C2 splitter reflux on profitability. Initially increasing reflux improves separation and thus profitability. However at high reflux the reboiler is against constraint and additional reflux increase involves a sharp decline of profitability. With good control the column can be kept precisely at the point of most optimal reflux. Another example, if one is needed is given in figure 2. The figure shows how C3 splitter bottom purity is affected by throughput. At increased throughput the column must operate at lower reflux ratios. Propylene purity can still be maintained but bottom purity suffers. Is it economical to increase the feed? Up to a point it is, but beyond that point loss of propylene to the bottoms and increased furnace fouling dictates a throughput limit. Good model based control would be able to identify the maximum economical throughput.

ic data from a number of plants, shows significant variations of operations of such columns, with adverse effects on product recovery and, often, plant throughput. Two examples will illustrate these effects.

### **Problem Statement**

This paper addresses a very simple and practical distillation control problem. The column of interest has one major distillate product and one bottom product. The feed, as well as each of the products, may contain several components. There are two control handles (manipulated variables): Product draw and reboiler heat duty. There may be onstream analyzers for measuring product compositions continuously, or - the laboratory may take measurements periodically. The column may have one or more tray temperature measurements. The feed comes in from a piece of equipment, upstream of the distillation column. Its composition and flow are not steady.

The control algorithm must find a way to set reboiler heat duty and top product draw such that both product compositions are steady and at their targets.

Figure 3 shows our example C2-Splitter. The column has a side distillate and a bottom product. It has also a pasteurization section, above the side draw, to rid the product of methane and inerts. Thus our C2 splitter column has two major control handles: product draw and reboiler-heat duty, and a minor control handle: vent flow. The typical column would be equipped with one or more on-stream analyzers, measuring product compositions continuously. There are five temperature measurements which could be used for inferential calculations.

### **Review of Past and Present Technology**

Distillation has been traditionally looked at as a two-by-two control problem, involving interactions between the two control objectives of maintaining top and bottom purities at their targets. Manipulating a control handle to correct top composition necessarily affects the bottom purity, and vice versa. In addition to the interactions, there are substantial dynamic delays between making a control adjustment and measuring its effect via the on-stream analyzers. The combination of interactions and dead-times - in the face of changing feed flow and composition, as well as other unmeasured conditions - renders the control problem difficult.

In early installations, computer control engineers attempted to solve the problem by configuring two standard control loops. One based on a bottoms purity analyzer measurement, manipulating reboiler heat; the other based on a top purity analyzer reading, manipulating distillate draw. Between the two loops there would be a "decoupler", which would make additional adjustments in the bottom loop to cancel out the top loop interaction, and additional adjustments in the top loop to cancel out the bottom loop interactions. In the more sophisticated configurations, the standard control loops would be replaced by Smith Predictors (1) which overcomes the dead time difficulty by predicting the dynamic response of the analyzer one dead time ahead.

Voluminous literature describes this package and its tuning, given the dynamic behavior of the column. As examples of this approach, refer to Shinskey (2) and Bartman (3). The control designs begin by obtaining empirical models of column and analyzer dynamics, and then setting decouplers and predictors.

During the eighties, following the tremendous computing progress, Industry has moved to a Multi-Variable Control (MVC) methodology (4), which combines predictive control and decoupling in one algorithm. MVC is more conveniently packaged, and in addition, it can deal simultaneously with column constraints and purity feedback control. But in terms of solving the two-by-two control problem, the two methodologies - a collection of single control and decoupling blocks, or MVC type designs - deliver similar control performances. Both rely on measuring the product qualities, applying predictive feedback to manipulate column conditions. Both employ linear, empirical process models, derived by a series of

tests where variables are perturbed to identify dynamic response of analyzer readings resulting from changes in manipulated or disturbance variables.

Hundreds of industrial distillation control applications use MVC, or other linear predictive feedback algorithms, to control product qualities. The success of this technology has, however, been mixed. In the authors experience, about one third of applications work well, another third work at times, while one third do not work at all (5). There are, at least, two reasons for the poor statistics, as follows.

a) The nonlinearity problem.

Distillation processes are notoriously nonlinear; superfractionators, in particular, change their process gains and dynamics substantially with operating conditions. For example, the effect of reflux on product purity is typically logarithmic, rather than linear. Figure 4 shows a similar effect for the settling time of the process. Other studies (6) have confirmed such non-linear a behavior.

Real life fractionators must vary their operating conditions to deal with changing flows and composition of feeds, weather effects on the condenser or unmeasured reboiler disturbances. Thus, their dynamic behavior may change from day to day. Model-based controllers, and especially dead-time compensators, are sensitive to the accuracy of their linear models. They work well when models reasonably agree with actual equipment responses. Models that predict the outcome of a step change with accuracy of  $\pm 20\%$ , in time or steady-state gain, are considered good. Less accurate models require a sacrifice of control performance in the form of detuning or "Move Suppression." If moves are not suppressed, responses could become unstable. As disagreements between the real process and the model grow, the control become sluggish and loses its effectiveness.

b) The slow feedback problem.

Analyzer response-time in a high-separation column could be 2 – 4 hours. That is the time elapsed between changing distillate draw and observing the analyzer response to that control action. The time between introducing a feed composition disturbance and analyzer measurement of the result of such a disturbance could be about 3 - 6 hours. Should a feed composition change occur, the controller would be oblivious to the disturbance for hours. Then it would respond by correcting the distillate draw, and if the control model is perfect, it would bring the products back to targets, about 7 hours after the disturbance had occurred. More realistically, such a disturbance might linger for a day.

To successfully handle columns with varying feed composition, advanced control must have a way to foresee unmeasured disturbances and correct for their effect early. Inferential control methods have been proposed, for forecasting product purity from available column measurements, which respond faster than analyzers. Initial attempts at inferential control, for example by Bartman (3), focused on certain tray temperature measurements as early indicators of feed composition change. Other workers, for example Tolliver (7), have analyzed column temperature profile to select the best location for such a temperature measurement.

These simple methods have worked well in conjunction with onstream analyzers, mostly in low reflux columns. Columns with high reflux have a more complex temperature profile, where interpretation of tray temperature measurement requires taking into account the liquid / vapor (L/V) traffic, pressure and, in multi-component situations, the off key component composition (8). While it is relatively easy to correct the temperature for pressure, it is much more difficult to correct it for L/V, and for unknown concentration of off-key components.

Much of the industry has resorted to a purely statistical approach for correcting the oversimplified tray temperature models. This approach employs regression analysis to fit a number of measurements into a distillation process model. Atique Malik (9) shows an example of such an approach. With the improvement of statistical tool and their development into Neural Networks in the early nineties, regression has become easier. However there are two practical problems with the regression-analysis approach:

a) Quality and volume of laboratory data.

Statistical models require large amounts of data. It is costly and difficult to generate such volume of data from reliable, well-controlled test runs. On the other hand, routine laboratory data is often in error because of the process not being at steady state at the time of sampling, and the way samples are handled. These errors can diminish the validity of statistical correlations.

b) Model validity range.

Statistical models tend to drift with operating conditions, and when process conditions approach the limits of the correlation region, the models become questionable.

The authors have therefore taken a different approach detailed by Friedman (8, 10). Given that distillation is a well known process, Friedman has applied engineering shortcut, steady-state models to infer and control distillation column dual product compositions. Such models are easy to set, and need minimal amount of data for calibration: two or three sets of test run data. Once calibrated, engineering, phenomenological models maintain their fidelity even when process conditions change drastically.

### **RMBC System**

This paper will extend the engineering modeling approach, and present the use of rigorous tray-to-tray models, for closed-loop control of distillation columns. The paper will show how rigorous distillation models deal with issues noted above: nonlinearity, feedback delays, and inferential prediction of product compositions.

We will also show that rigorous models can account for other control problems such as correctly predicting column constraints, optimizing operating conditions where extra degrees of freedom exist, and finally, identification of erroneous instrument readings.

Figure 5 is a schematic illustration of how RMBC works. We will describe it below module by module.

1. Process measurement reading.

We start by reading all available process measurements: flows, pressures, temperatures, analyzers and possibly some levels. The frequency of readings depends on the column dynamics. In the case of our example C2 splitter, reading of fresh data takes place every five minutes. Typically reading is done via a DCS interface database such as PI (a plant information system of OSI Software, Inc.).

2. Dyncorr.

We pass the input measurements through a dynamic correction module: Dyncorr. The purpose of this routine is to predict what the steady state values of the measurements would be if control handles and disturbances were to remain constant at current values. The dynamic model in Dyncorr is a close approximation of a rigorous tray to tray dynamic model. include multivariable / controllers (MVC).

3. Minfrac.

Minfrac is a steady state rigorous tray to tray simulation. Minfrac starts with the feed composition identified one run (five minutes) ago. It takes the current control positions (flows and pressures), and produces steady state values for column temperature profile and product purities.

4. Optimizer.

The set of steady state measurements produced by Dyncorr, and the set of values simulated by Minfrac should be equal. To the extent that there are differences, this must be due to a change in feed composition, an unmeasured disturbance, or sometimes simply an erroneous measurement.

The optimizer is charged with comparing the two sets, re-identify the feed, and check also for outliers which indicate unreliable readings. This reconciliation is accomplished by minimizing squares of the differences. To the extent that there are degrees of freedom this same optimizer also finds the best positions for these variables. In our C2 splitter example we permit changing the column pressure as an extra degree of freedom.

5. MVC.

Moving of the manipulated variables is done via a standard MVC controller. RMBC can accommodate any MVC package, though we will show that some packages perform better. The MVC receives its control variables in the form of inferential calculations from Minfrac. Possibly it receives other constraints and information from the DCS. The MVC has a dynamic model of the column, which help determine the correct timing of the manipulated variable actions.

6. Dynstill.

We discussed two dynamic models, that of Dyncorr and that of the MVC. We discussed also the nonlinear nature of distillation dynamics and that for good control the linear models should be reset when the column conditions swing. RMBC has the ability to re-

calculate the dynamic models through its module Dynstill. Dynstill is a rigorous dynamic simulation the column, including hold-ups, downcomers, reboiler, accumulator and all basic control loops. It generates the dynamic models by making step changes in the manipulated variables and running the dynamic responses to those changes.

### **Minfrac and Dynstill features**

We discussed the modules of RMBC. The key element, or engine, in this system is a tray-to-tray distillation program Kes, which can be configured as a steady state or dynamic tool. We will now explain the features of this program in more detail.

The program formulates the MOSH equations (material balance - components and overall; summation of mol fractions, and heat balance) of each tray, as a function of the unknown component mol fractions, vapor / liquid flows, and temperatures. The equations are linearized and their partial derivatives arranged in a block-tri-diagonal Jacobian. The Jacobian is then inverted, and delta's of the variables are calculated. The equations are then relinearized, and the process of inversion repeated until the delta's are driven essentially to zero. This is the Newton-Raphson approach used in prior work by Naphtali-Sandholm (11), which is consistent with the so-called "open-equation" format. Kesler et al (12), have further modified this approach - by component and tray aggregation - to significantly increase its stability and speed. Further, in the Kesler formulation, Kes generates analytically a great number of first and second-order derivatives required in optimization and/or in control applications. It should be noted that numerical differences - besides being awkward to generate one-at-a-time - are not sufficiently accurate for these applications.

This formulation has important advantages in RMBC. First, the inverse of the Jacobian can be readily used to calculate simultaneously precise effects of changes in the right-hand side coefficients, such as feed compositions, on a variety of other variables of the problem. Second, the formulation makes it possible to add on the right-hand side holdup terms required for dynamic calculations. Third, additional equations and variables, dealing with control, can be added in the formulation without disturbing the rest of the matrix; the whole system can, then, be solved with little extra computational effort, using matrix partitioning methods such as shown by Goldstein-Stanfield (13). Fourth, without numerical derivatives convergence is well behaved and the program is robust. Fifth, it is fast both in steady-state and dynamic modes of calculation, consistent with the on-line, closed-loop requirements of the applications. Our example C2-Splitter converges in 1-2 seconds on a 233-MHz PC.

### **More about Inferential Feed Identification**

We explained that the RPBC package runs once every few minutes, five in our C2 splitter example. Minfrac starts with the feed composition that it identified one run earlier, and current control settings of column pressure, distillate flow and reboiler-heat duty. It then

computes an "expected" column temperature profile. Expected in the sense that if the model is entirely correct, and the feed identified five minutes earlier has not changed, the calculated temperature profile would precisely match the measured tray temperatures, as well as bottom, top and accumulator temperatures.

The optimizer applies a least-square optimization to correct the feed, utilizing more temperature readings than feed-composition adjustments. Should a temperature reading be erroneous, the least-squares routine would identify that temperature as an outlier and ignore it.

We have thus far spoken only about reconciling temperature profile against feed composition. But we are not limited to temperatures. In columns equipped with on-stream analyzers, RMBC considers also the analyzer signals for reconciliation. On one hand Dyncorr can read the current analyzer signal and correct it to future steady state value. On the other hand Minfrac computes product compositions. Thus, the optimizer can reconcile the feed not only against temperatures but also against analyzer readings. Should the analyzer read incorrectly, as analyzers sometimes do, the optimizer would identify the analyzer reading as an outlier and ignore it. This additional reconciliation imposes negligible extra computational effort.

Most current technology handles analyzer feedback by special-purpose dynamic predictors, which assume the analyzer signal always takes priority over inferential calculation. Here we have come up with a scheme to eliminate the special purpose predictors and treat the analyzer as valid only when its reading can be explained.

### **RMBC And The MVC Controller**

This section describes use of RMBC in conjunction with an MVC package. Figure 6 shows how the MVC works on sample-problem C2-Splitter. The MVC has the two product compositions and flooding constraint as control variables, and reboiler heat and distillate draw as manipulated variables. In addition we permit two minor manipulated variables: C1 venting and column pressure.

The Review of Technology section discussed one of the difficulties of applying MVC technology to distillation columns. Namely, MVC relies on dynamic models, which are identified a priori by perturbing the column at a given set of operating conditions, whereas many distillation columns do not have constant dynamics. This model inadequacy diminishes control performance.

In the RMBC environment, the rigorous dynamic program Dynstill can re-identify the dynamics for the current operating conditions, without any plant test. The new dynamic response can then be fed into the MVC model-matrix without disturbing the controls. Not all commercial MVC packages can accept model changes "on the fly", but some can. Details of how RMBC transfers information to MVC are given below.



In the MVC world, models are identified as sets, or vectors. Each set describes the time-response of one control variable to a unit change of one manipulated variable. An illustration of such a response is shown in figure 7. For example, the response of control variable C(J) to a unit step in manipulated variable M(L) is:

$$\Delta C(J,K+I) = D(J,L,I) \quad [1]$$

K = The time increment at the start of the manipulated-variable step.

$\Delta C(J,K+I)$  = The change of control variable C(J) I time increments after the step

$D(J,L,I)$  = A vector describing the response of C(J) to a unit change in M(L). It is a finite vector of say 60 elements, which indicates that this response is fully completed in 60 time increments or less. In our example of five minutes per time increment the open loop response would take up to five hours. Thus  $D(J,L,60)$  is the steady state gain for that process.

In a typical control situation, a series of changes are made to M(L).

Applying superposition, the change to C(J) would be:

$$X(J,L,K) = D(J,L,60) * M(L,K-60) + \sum_{I=1}^{60} \Delta M(L,K-I) * D(J,L,I) \quad [2]$$

K = The present time.

$X(J,L,K)$  = The dynamic influence of M(L) on C(J) by superposition.

$M(L,K-60)$  = The control position of M(L) sixty time increments ago.

$D(J,L,60)$  = The steady-state process gain for this process. Since the response is fully finished after 60 increments  $M(L,K-60)$  is multiplied by the gain, whereas control moves which took place less than 60 increments ago are multiplied by the dynamic coefficient  $D(J,L,I)$ , which is normally less than the gain.

$\Delta M(L,K-I)$  = The change of manipulated variable M(L) I increments ago.

$D(J,L,K-I)$  = The dynamic influence of M(L,K-I) at time K.

The incremental form of equation 2 is equation 3:

$$X(J,L,K+1) - X(J,L,K) = \sum_{I=1}^{60} \Delta M(L,K-I) * \Delta D(J,L,I) \quad [3]$$

$\Delta D(J,L,K-I)$  = The dynamic difference vector:  $D(J,L,I) - D(J,L,I-1)$

The response of C(J) would be the sum of all manipulated variables which affect it:

$$C(J,K+1) - C(J,K) = \sum_L X(J,L,K+1) - \sum_L X(J,L,K) \quad [4]$$

$\sum X(J,L,K)$  = The influence of all manipulated variables on C(J). It should trend with

C(J) and the difference between them would be constant if the dynamic model D is accurate. Taking the difference equation eliminates that bias.

C(J,K) = The reading of control variable C(J) at time increment K.

C(J,K+1) = The prediction of control variable C(J) one time increment into the future.

In terms of the control moves:

$$C(J,K+1) = C(J,K) + \sum_{L,I} \text{Delta } M(L,K-I) * \text{Delta } D(J,L,I) \quad [5]$$

Equation 5 provides a way to predict the reading of C(J) one time step (K+1) into the future. MVC's need to forecast the result of their control actions 60 times into the future, and to do that, equation 5 is extended, to give:

$$C(J,K+N+1) = C(J,K+N) + \sum_{L,I} \text{Delta } M(L,K+N-I) * \text{Delta } D(J,L,I) \quad [6]$$

N = The number of future time increments. By varying N from 0 to 60, the behavior of C(J) can be forecasted through the complete time horizon of the MVC.

Delta M(L,K+N-I) = The control move of manipulated variable M(L) at time increment K+N-I. If N-I is negative, Delta M(L,K+N-I) is a past control action. If N-I is positive, Delta M(L,K+N-I) is a future control action. If N-I is zero, Delta M(L,K+N-I) is the control action to be applied at the current time increment.

An explanation is in order of how the MVC determines its control actions.

The MVC formulates a constrained optimization problem. The constraints in this set-up are future readings of the control variables, which should, preferably, respond following a certain desired pattern, and approach their target at steady state at the end of the time horizon. The unknowns to be solved for are the control moves. The specific mathematical programming of this problem, differs among the MVC products, and the details are usually confidential. Suffices to note that the control problem set-up is based on equation 6. If equation 6 can accept model changes without upsetting the predictions – then this MVC can accept continuous model changes from a rigorous distillation program, as envisioned here.

The beauty of equation 6 is in its separation of past events from future events. The current measurement C(J,K) summarizes everything that happened in the past, including incomplete influence of past control actions. Suppose we notice an imperfect model and change coefficients Delta D(J,L,I) at time K. Equation 6, then, still accepts the current

$C(J,K)$  as a given, ignoring past, erroneous predictions for it. The new coefficients participate only in the prediction term:  $\Delta M(L,K+N-I) * \Delta D(J,L,I)$ , which calculates the future influence of manipulated variable movements. Even when  $N-I$  is negative, the term

$\Delta M(L,K+N-I) * \Delta D(J,L,I)$  denotes the future influence of past control moves.

Dynstill is well suited to compute the coefficients  $\Delta D(J,L,I)$  of equation 6. The program begins with current steady-state operating conditions. It, then, steps the manipulated variables, one at a time, and goes through the dynamic model to compute the response coefficients  $\Delta D(J,L,I)$ . Figure 8 illustrates sample output of the dynamic responses.

We can thus eliminate the tedious process of identifying and validating the MVC models. Of course, there is a need to validate and calibrate the time-dependent the dynamic program Dynstill. However, once calibrated under one set of operating conditions, Dynstill can recalculate the dynamic model at other conditions. Recalibration of Dynstill would only be needed after unusual changes of operations or equipment.

## **Conclusions**

We have discussed a novel format RPBC for controlling distillation processes. This format makes use of rigorous models to provide precise solutions for distillation control. We have shown that RPBC not only tackles the theoretical issues of inferential calculation, analyzer feedback and column optimization with ease, it also handles the practical problem of occasionally incorrect instrument or analyzer readings.

In terms of implementation effort, RPBC is a labor saving system because it is based on standard algorithms, configured in matter of hours. It replaces the labor-intensive task of testing and re-testing for empirical process dynamic model by a dynamic tray to tray model, which needs only a one-time calibration.

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### Optimization economics

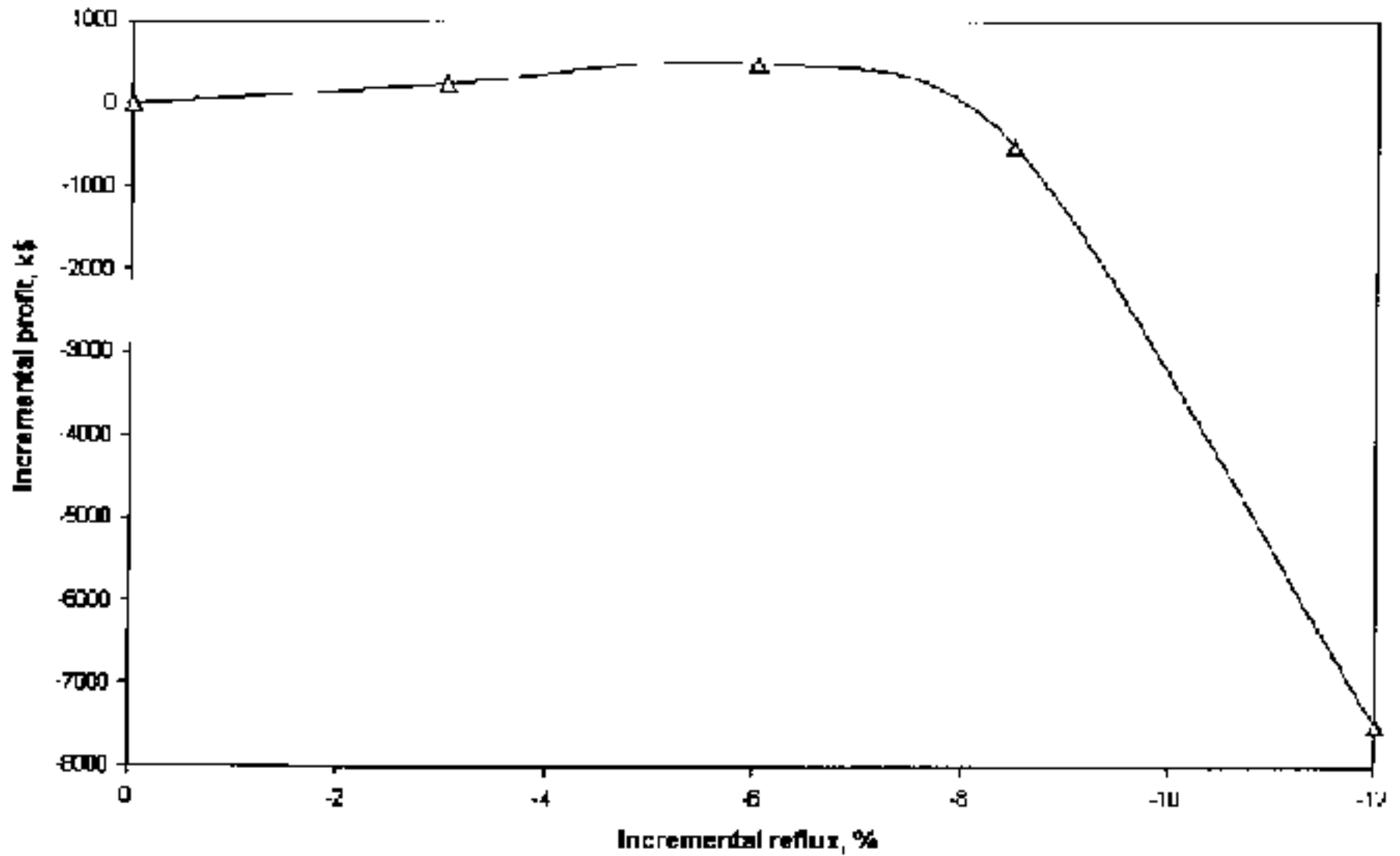


FIG.1: EFFECT OF CO<sub>2</sub>-SPLITTER REFLUX ON PROFITABILITY

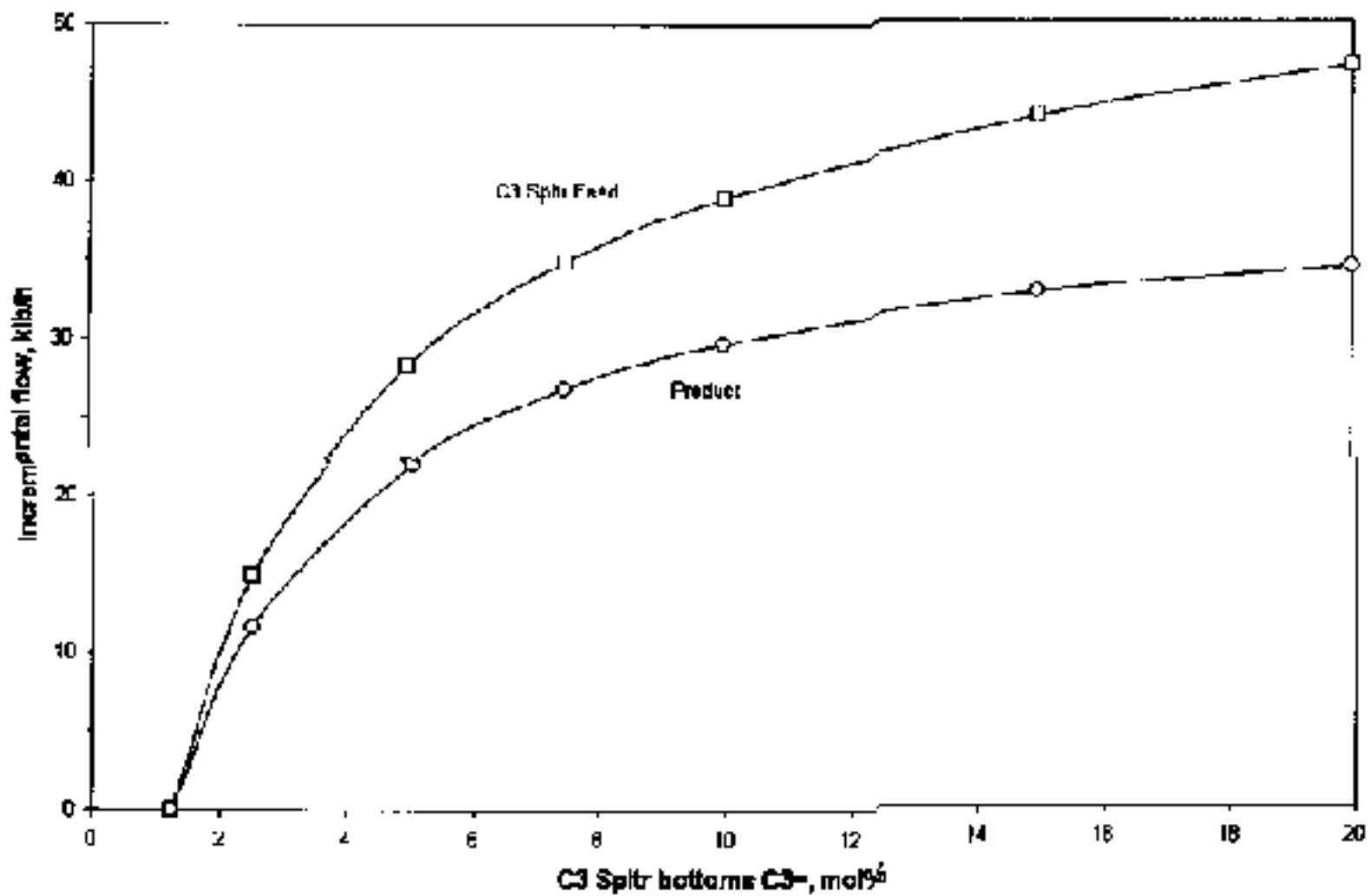


FIG. 2: EFFECT OF C3= BOTTOMS REJECTION ON C3-SPLITTER THROUGHPUT AT MAXIMUM COLUMN LOADINGS

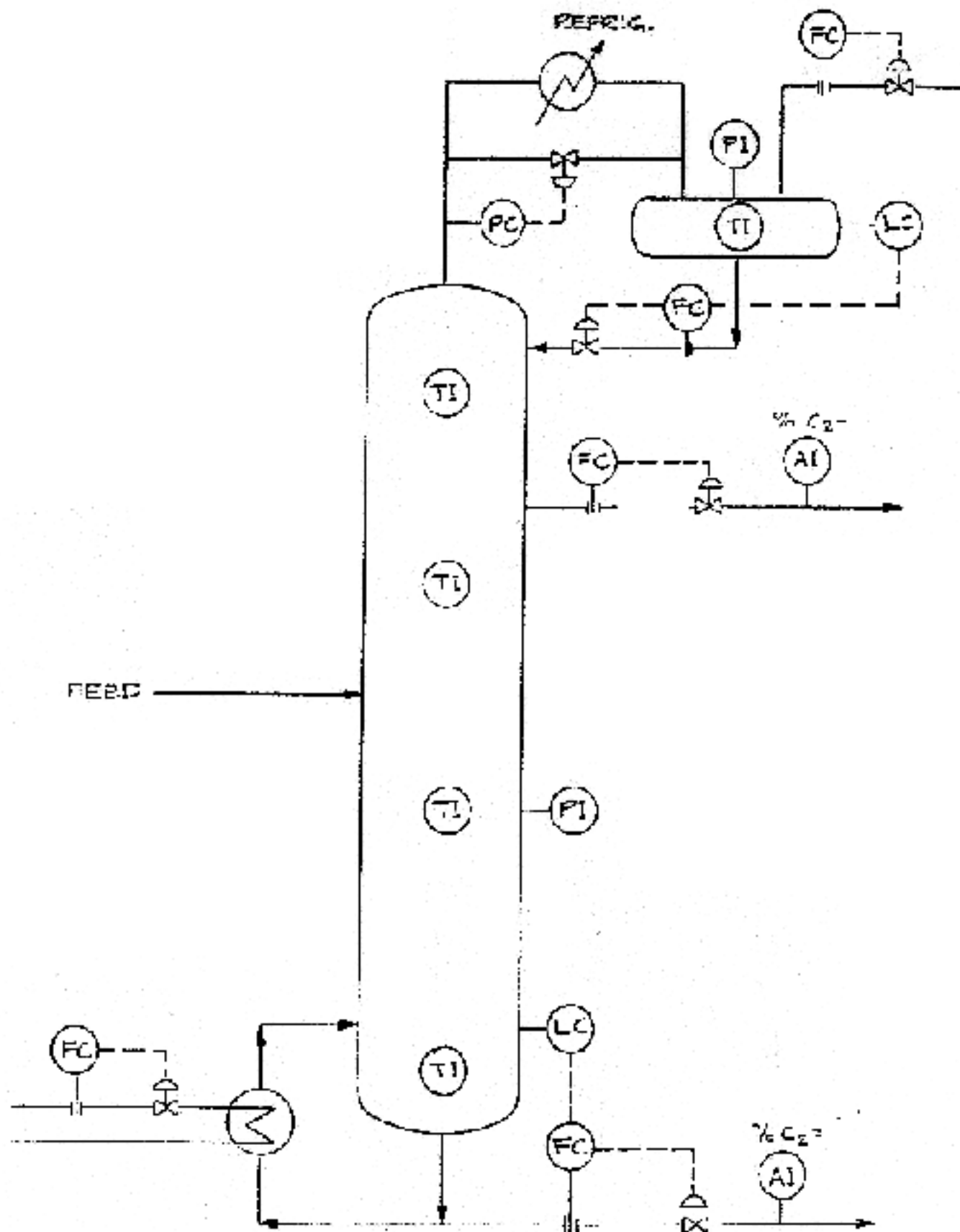


FIG. 3. SAMPLE PROBLEM: CO<sub>2</sub>-SPLITTER

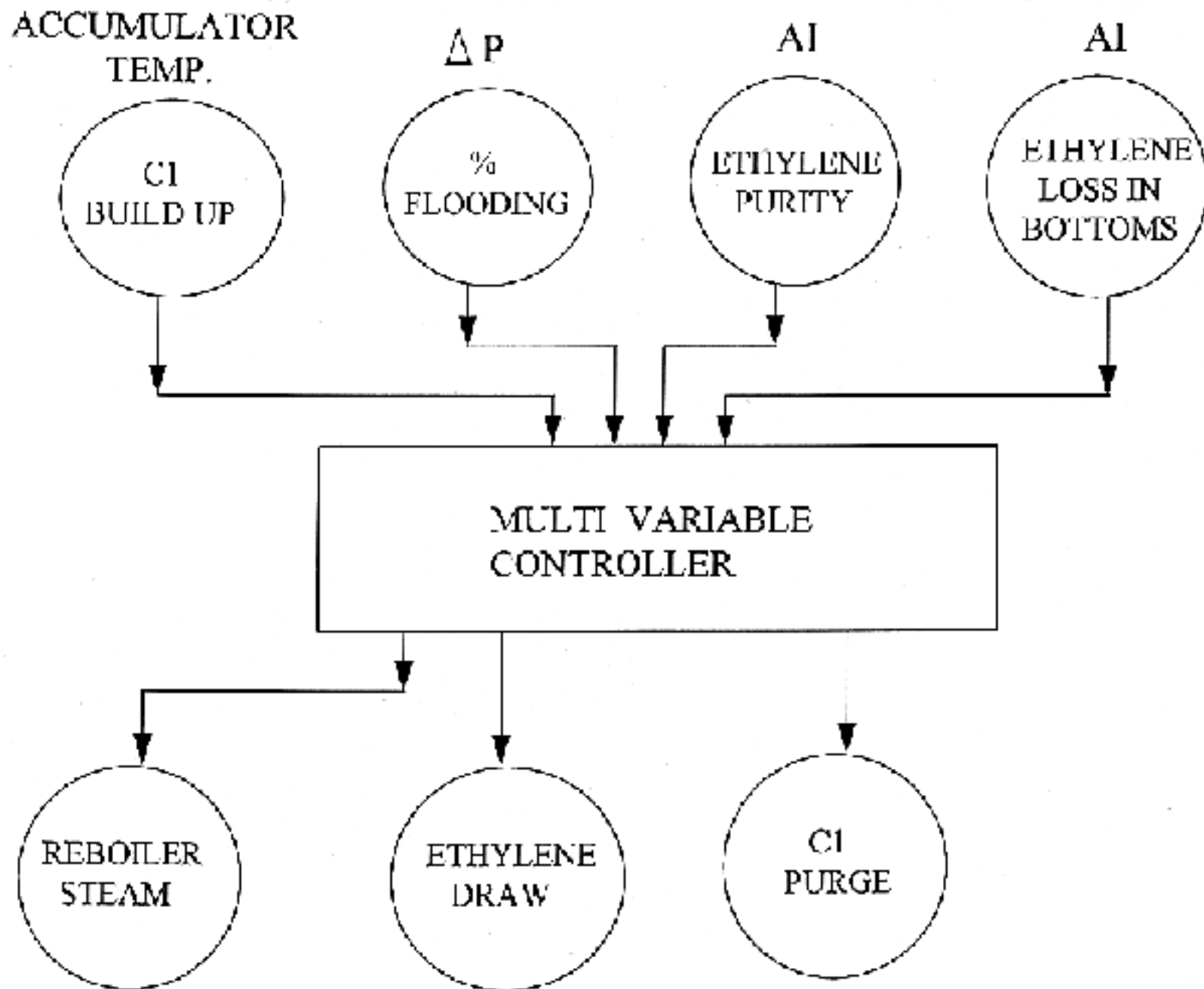


FIG.4: TYPICAL C2-SPLITTER MVC STRUCTURE



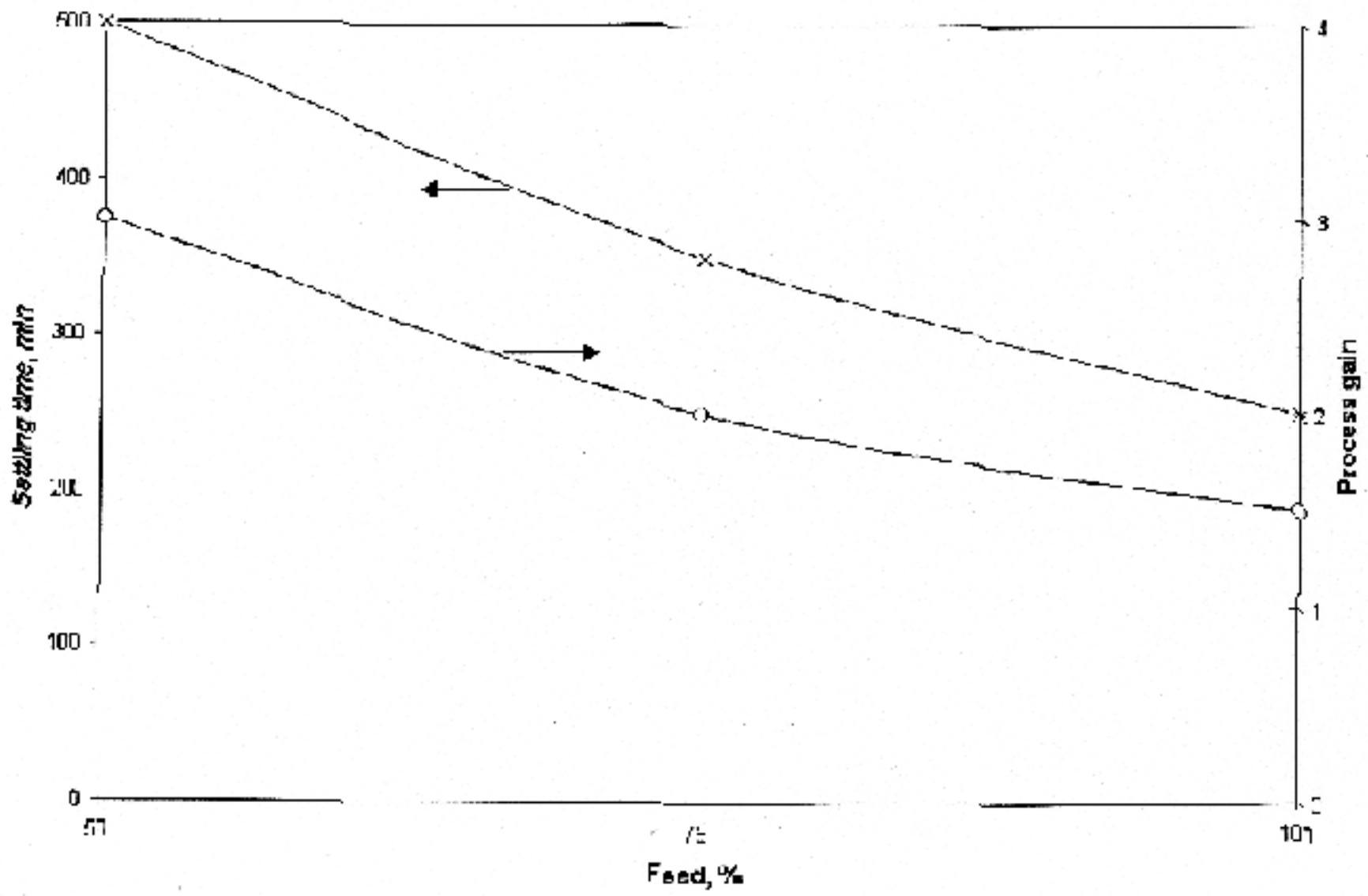


FIG. 5: SETTLING TIME AND PROCESS GAIN VS. THROUGHPUT IN A CO<sub>2</sub>-SPLITTER

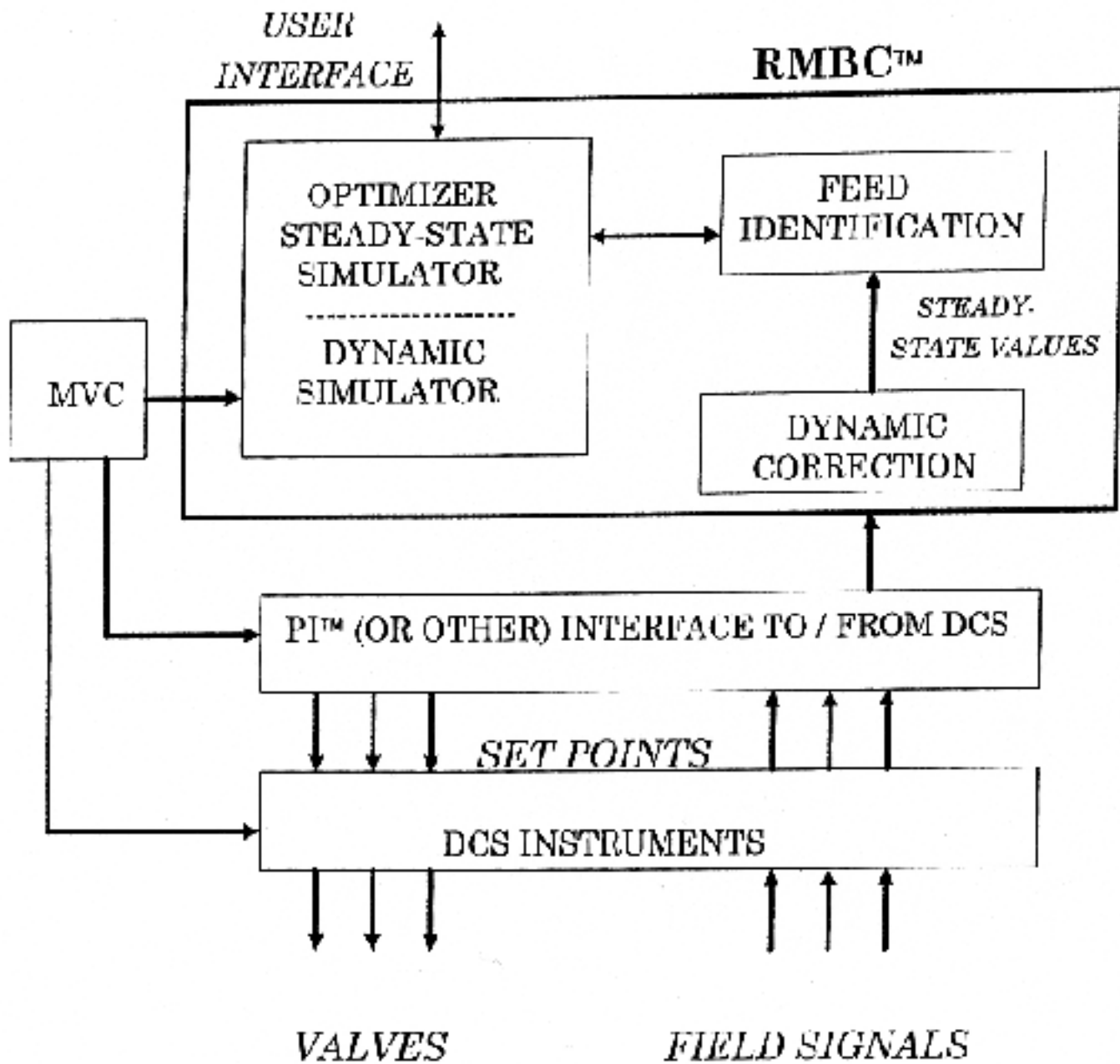


FIG. 6: SCHEMATIC OF RMBC™

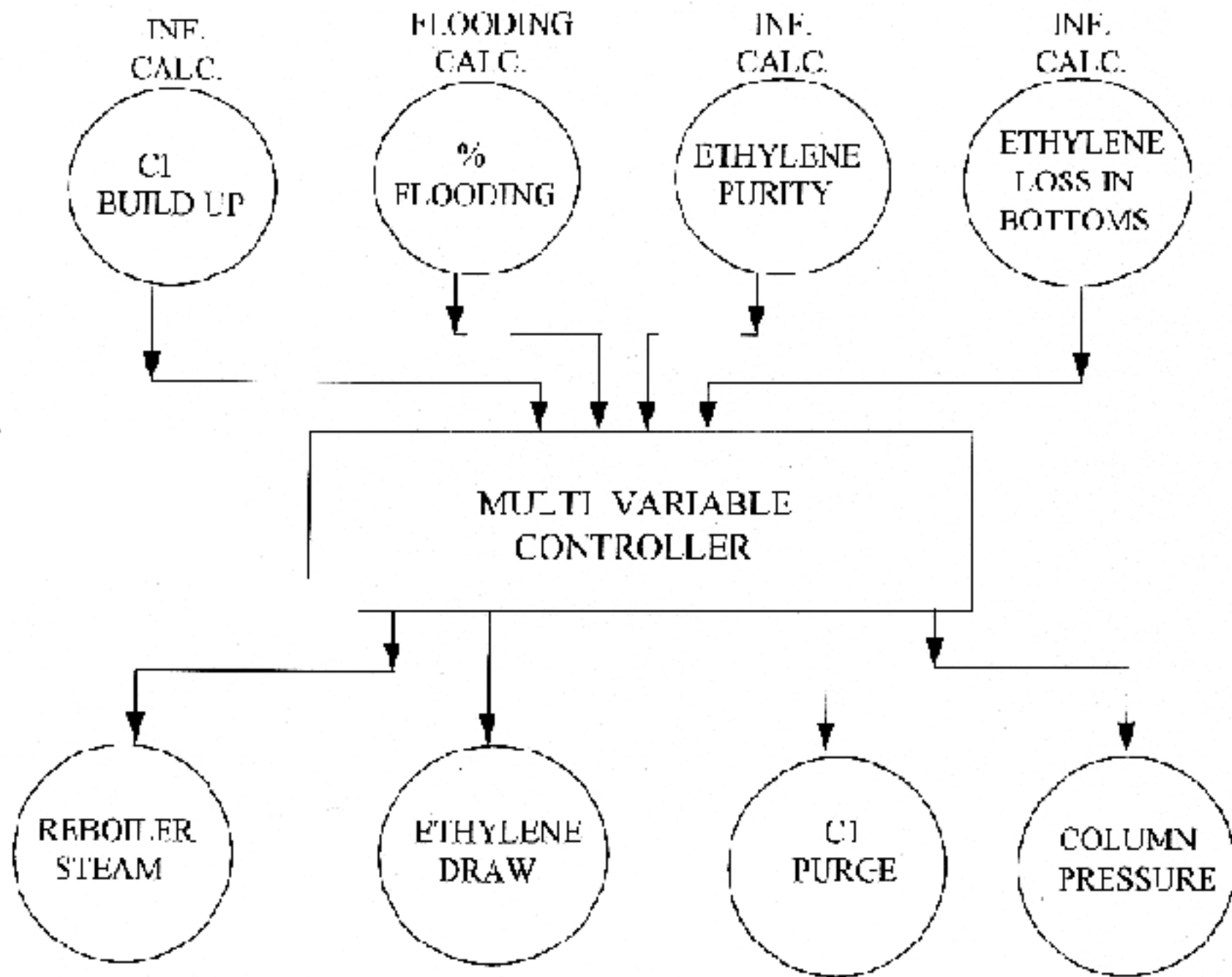


FIG. 7: MVC STRUCTURE UNDER RMBC

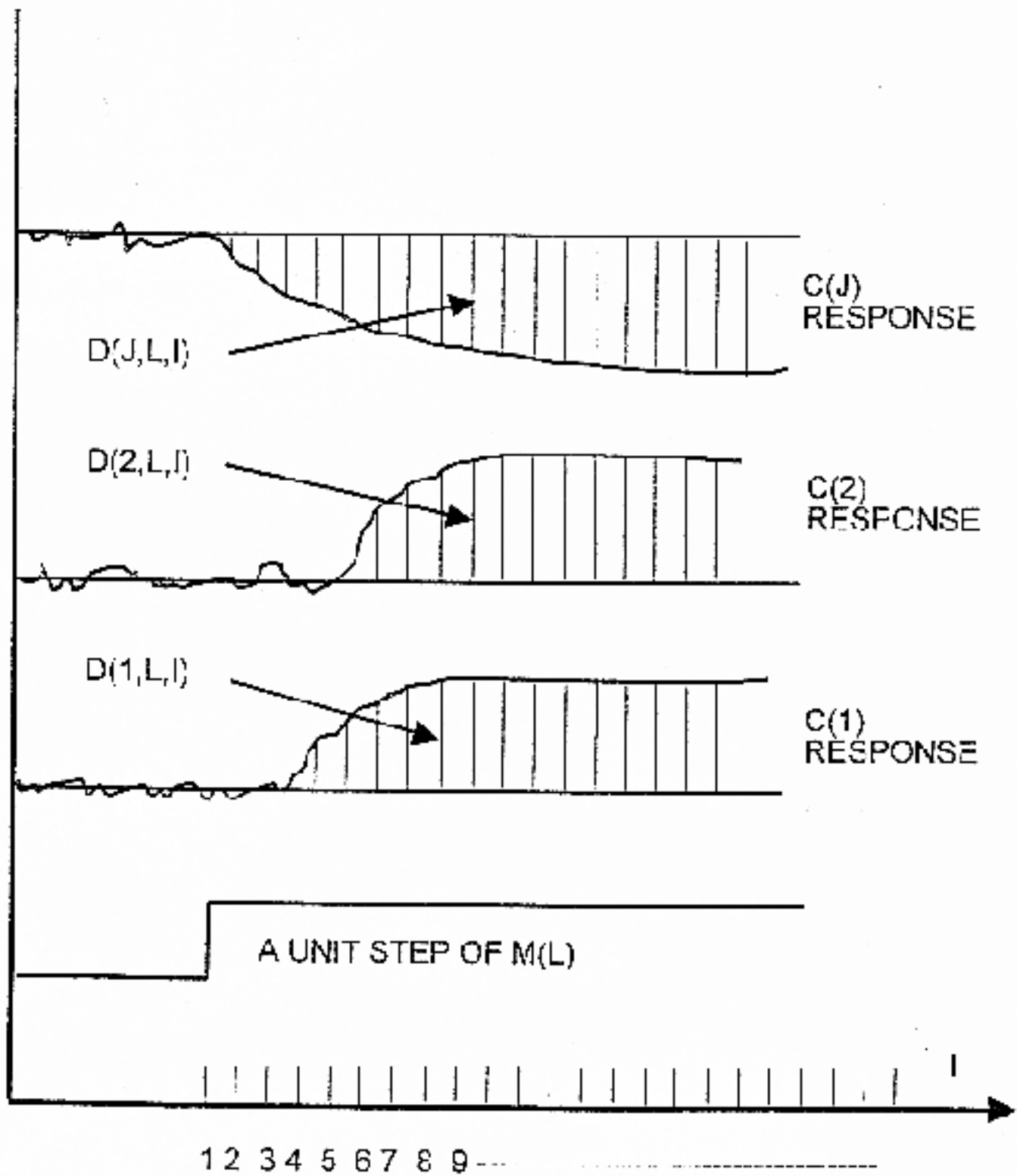


FIG.8: GRAPH C REPRESENTATION OF THE DYNAMIC MATRIX

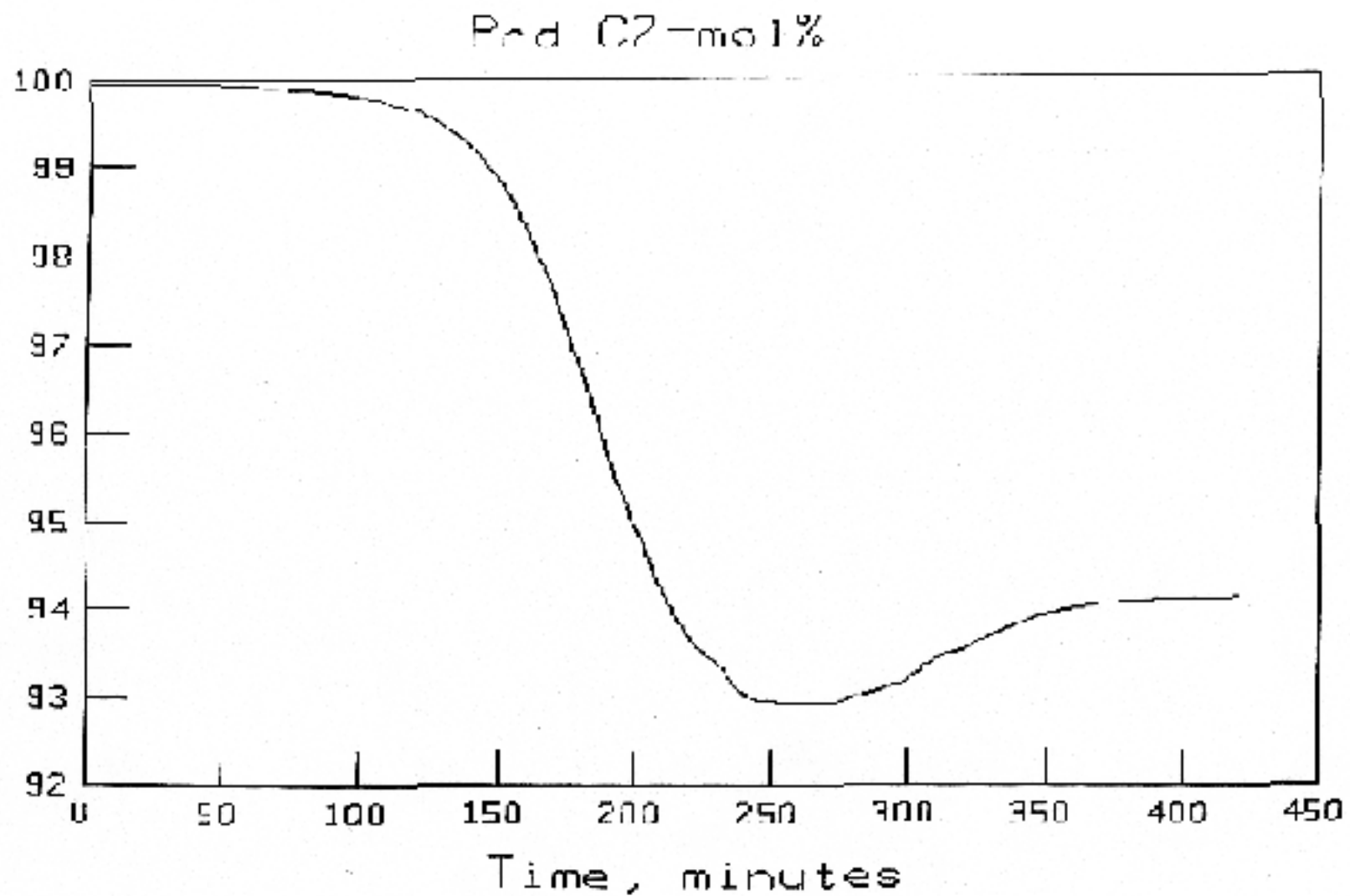


FIG.9: PRODUCT PURITY IN RESPONSE TO 10% Δ C2 IN FEED TO C2-SPLITTER