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Department of Chemical Engineering

ENERGY OPTIMISATION AND CONTROLLABILITY IN COMPLEX DISTILLATION COLUMNS

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CHAPTER 5. DYNAMIC MATRIX CONTROL APPLIED TO THE DIVIDED WALL COLUMN

5.1 Abstract

In this chapter, the use of Dynamic Matrix Control (DMC) for composition control in the DWC is studied. The performance of DMC for different tuning parameters is analysed. DMC strategy is compared to decentralised feedback control. Simulations are done to study the performance of both control strategies for disturbance rejection and setpoint tracking. Different control structures are considered but basically, the control structure consisting in the stabilisation of the column by D and B and the composition control by L, S, and V is studied.

5.2 Introduction

High purity quality, efficient use of energy, and environmental requirements impose strict demands on control systems. As response to these challenges, control methods that use a model of the process as part of the controller have been developed. One of these methods, which has succeeded in industry, is the DMC. In the distillation domain, DMC is appropriate for multicomponent and restricted distillations (Luyben, 1992).

DMC is classified as Model Predictive Control (MPC). MPC is the class of computer control schemes that utilise a process model for explicit prediction of future plant behaviour and computation of appropriate corrective control action. The conventional consensus among industrial and academic researches is that MPC is typically best suited to processes with any combination of the following characteristics (Ogunaike et al., 1994):

- MIMO variables with significant interactions between SISO loops
- Complex and unusual problematic dynamics such as long time delays, inverse responses, or large time constants
- Constraints in input and/or output variables

The DWC performs a multicomponent distillation, it is a MIMO system with significant interactions between SISO loops, it has inverse responses, large time constants, and may have long time delays. All these are reasons that motivate the study of MPC application to the DWC.

Although the ability to handle constraints directly has been one of the most significant contributions to the MPC success in industrial applications, in this work, constraints will not be considered.

Control design methods tend to produce controllers of a complexity proportional to the plant model complexity. If the model is complex, control designs more complicated than necessary may be obtained. Because of that, it is always appropriate to consider simple models first.

DMC is a MPC scheme that uses a very simple model, a linear model. Linear models are very well suited to MPC because robust and reliable software is available to solve the optimisation problem. The basic idea in DMC is to use a time-domain step-response model of the process to calculate the future changes in the manipulated variables that will minimise some performance index. Since the calculated control action depends on all controlled and manipulated variables, the DMC is a centralised control strategy. DMC is a feedforward control strategy, which may actuate before the setpoint error appears.

The performance of DMC in simple distillation columns was studied and compared to the performance of the decentralised feedback strategy by Georgiou et al. (1988). The authors concluded that for moderate purity columns (around 0.99 molar), the performance of DMC was better, particularly for setpoint changes. However, strong non-linearity of high-purity distillation columns were found to limit the application of DMC to relative small ranges of operating conditions.

For all that has been said, there are many reasons to believe that the DMC performance could be superior to that of the diagonal feedback strategy for the composition control of the DWC for moderate purity products. However, with DMC, a linear model will be used to predict outputs of a very non-linear system, giving an erroneous prediction of the real process behaviour. Besides, DMC is inherently a discrete control strategy. Controlling compositions, the time step can not be as small as desired because the composition measure is time consuming. This fact prevents quick initial responses. Finally, interaction between loops may be favourable in some cases in what decentralisation is preferred. The main objective of this chapter is the comparison between DMC and decentralised feedback control for composition control in the DWC.

5.3 Description of the programmed Dynamic Matrix Control

DMC has been programmed using MATLAB (MATLAB, 1998). Two separated blocs constitute the control system program. In one bloc, the model is built. The other block contains the control algorithm itself and the computation of the control actions.

5.3.1 Process identification and the model

The model used in DMC consists of a matrix called $\boldsymbol{B_n}$. This matrix contains the information of the open-loop process identification. Identification is performed applying step changes to the manipulated variables. A step change is applied to each manipulated variable at a time and the output profiles are registered. Output profiles are made of n points separated a time interval of Δt. Δt is the basic time unit of the control system.

There is an identification profile for each input (manipulated variable)-output pair. $\boldsymbol{B_n}$ is built of these profiles. Therefore, $\boldsymbol{B_n}$ contains the responses of all outputs to all manipulated variables and this way, interactions are taken into account by the model. Since the model is linear, an output response is calculated as the sum of the responses to the different manipulated variables actuating alone.

In order to have simple matrix calculations for the control action, $\boldsymbol{B_n}$ is built in such a way that, for each input-output pair, there is a sub-matrix of dimension nxm, where m is the number of steps in the control action (Ogunaike, 1994).

Therefore, three parameters are required to do the identification and build $\boldsymbol{B_n}$: Δt, n, and m. However, if the process studied is non-linear, the steps for the process identification have a large influence on the model obtained. The size and sign of these steps have to be decided carefully.

5.3.2 DMC algorithm

The programmed DMC algorithm consists in the following steps, which are repeated every Δt.

1. Reception of the measured output values from the process.
2. Calculation of the differences between the predicted and the measured output values.
3. Movement of the considered time frame by Δt.
4. Calculation of the error. The error is the area between the predicted output profiles without further control action and the setpoints. Only the first p points of the predicted output profiles are used to define this area.
5. Calculation of the manipulated variables profiles that minimise the area between the predicted output profiles and the setpoints. The expression for this calculus is given in equation 5.1. Profiles of m points are calculated.
6. Application of the first step of the control action to the process.
7. Calculation of the predicted outputs supposing that there is no further control action (the predicted outputs depend on the past control actions).
8. Correction of the predicted outputs with the differences found in 2.

DMC works with deviation variables (differences between actual values and nominal values). The outputs of the process enter the DMC as deviation variables and the manipulated variables exit the DMC as deviation variables. For this reason, the graphics in this chapter show deviation variables. In equation 5.1, the expression for the control action is given, where *du* contains the manipulated variables profiles in deviation form, *e* is the error, $\boldsymbol{B}_p$ is a matrix similar to $\boldsymbol{B}_n$ made with profiles of *p* points ($p<n$), and λ is a matrix of move suppression factors (detailed description of λ will be given in section 5.3.3.)

$$du = (\boldsymbol{B}_p{}'^{*} \boldsymbol{B}_p + \lambda) \setminus (\boldsymbol{B}_p{}'^{*} e) \qquad (5.1)$$

5.3.3 Tuning parameters

Recollecting the different DMC parameters that have appeared up to now, they are: Δt, *n*, *m*, *p*, and λ. They may be considered tuning parameters in the sense that they all influence the performance of the DMC. Little DMC literature offers guidelines on the selection of these parameters and most of the guidelines concern SISO systems. DMC has many adjustable parameters and appropriate values of some of them depend on the others. For these reasons, the DMC tuning is not an easy task.

5.3.3.1 Sampling interval Δt

DMC is a discrete control strategy. The sampling interval Δt is the basic unit of time. Every Δt, output values are measured, and new control actions are computed and applied. Δt is also the time between the points of the identification profiles.

For good closed-loop performance, the sampling interval has to be small enough to capture adequately the dynamics of the process. On the other hand, Δt has to be large enough to permit the on-line computations and output measurements.

5.3.3.2 Identification horizon *n*

The identification horizon *n* is the number of points in the identification profiles. Its value is related to the time needed by the open-loop system to achieve steady state. Specifically, *n* is chosen such that $n{*}\Delta t$ covers the time needed by the slower output to achieve steady state in open-loop (Marlin, 1995) (Georgiou et al., 1988).

The identification horizon is not considered a tuning parameter. However, it plays an important role in the control performance. *n* sets the longitude of the output predictions and for small *n* (short predictions), constant values assumed following the predicted values damage the DMC performance.

5.3.3.3 Prediction horizon *p*

The prediction horizon *p* is the number of points in the predicted outputs used to calculate the error. *p* also defines the size of $\boldsymbol{B}_p$, used to calculate the manipulated variables (see equation 5.1).

Δt^*p should be similar to the time needed for the closed-loop system to approach steady state. Typical p values range from 20 to 50 (Marlin, 1995). For linear systems, longer prediction horizons tend to produce less aggressive control action, less overshoot, and slower response. Longer prediction horizons also diminish the sensitivity to disturbances.

5.3.3.4 Control horizon *m*

The control horizon m is the number of points in the profiles of manipulated variables. Although only the first movement calculated is implemented, at every time interval, more than one manipulated variable movements can be calculated. m one-fourth to one-third of p are typical values (Marlin, 1995). Values from 1 to 6 are usually chosen (Shridar et al., 1997). In general, m should be larger than the time required for the slowest open-loop response to reach the 60% of the steady state (Georgiou et al., 1988).

For linear systems, shortening the control horizon relative to the prediction horizon tends to produce less aggressive controllers, slower system response and less sensitivity to disturbances.

5.3.3.5 Move suppression factor: *k2* and λ

The main tuning parameter is the move suppression factor, *k2*, which controls the trade-off between the amount of movement allowed to the manipulated variables and the rate at which the output deviation from setpoint is reduced over the prediction horizon. Different penalty weights can be applied to each one of the manipulated variables. In this case, a diagonal matrix called λ is used instead of *k2*. The diagonal elements of lambda are the move suppression factors of each manipulated variable.

Some authors say that the order of magnitude of *k2* has to be the same that the order of the $B_p{}'{}^*B_p$ diagonal elements (McIntosh et al., 1991). Increasing *k2*, a more robust control is obtained. The effect is very similar to that of shortening the control horizon relative to the prediction horizon.

5.4 Use of DMC for the composition control of the DWC

As was considered in the previous chapter, composition control objective is the control of A, B and C components compositions in the three DWC products. It is assumed that the inventory control is solved in a lower control level by two proportional controllers.

DMC requires three manipulated variables for the control of the three products purity. The set of possible manipulated variables is *L*, *V*, *S*, *D*, *B*, *SPLITD*, and *SPLITB*, removing the variables used for inventory control.

In this chapter, DMC is applied to non-linear models of different DWC distillation processes: identification profiles are taken from the models, control actions are applied to the models, and output values are obtained from the models. The non-linear models are the same used for simulations in the previous chapter, and described in section 4.3.1. A delay of 0.5 min is added to each output variable to simulate the time of measure.

MATLAB (MATLAB, 1995) is used to perform the control simulations connecting the distillation process (non-linear model) with the DMC system. In Figure 5.1, the flowsheet of the whole system is shown for an example where *L*, *V*, and *S* are the manipulated variables. "dwc_s_a" contains the DWC non-linear model and "mpcbloc_a" contains the DMC algorithm.

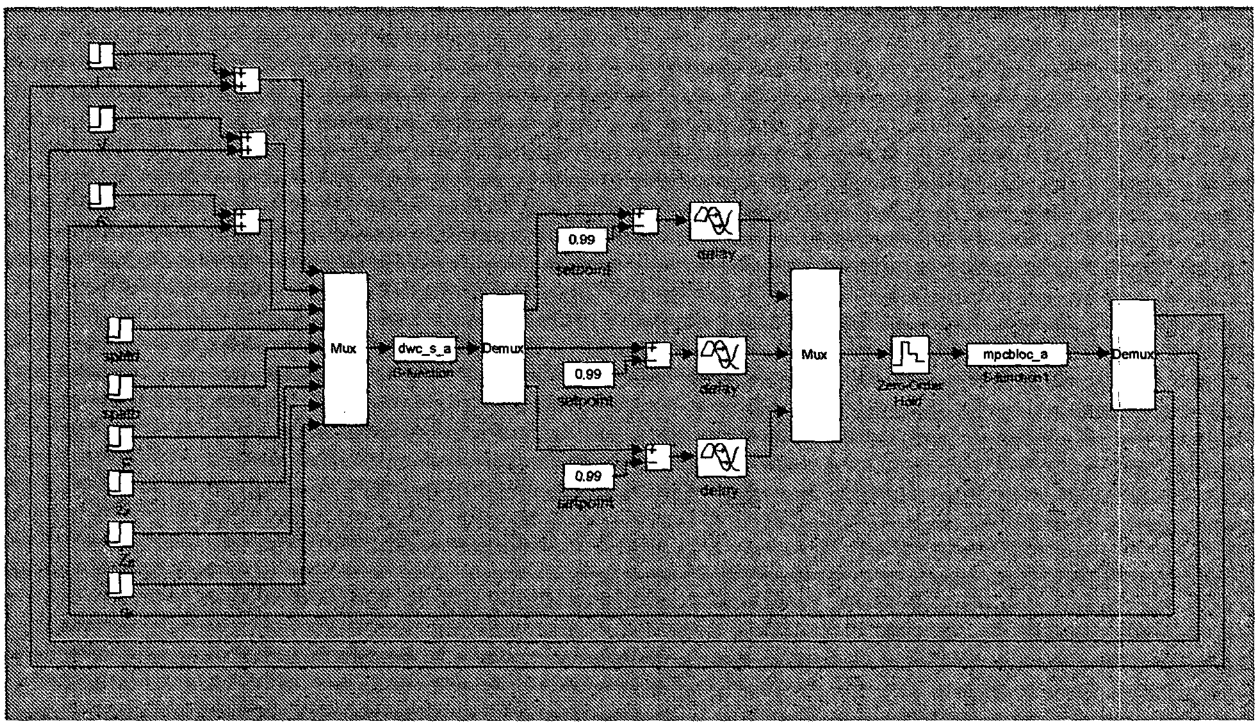

Figure 5.1: example flowsheet of the DMC application to the DWC

5.5 Identification of the DWC system

In this section, the identification of the DWC distillation process is studied. Problems derived from the non-linearity of the process are discussed. As indicated, the identification of the stabilised DWC is done (identification is done with inventory control loops closed).

5.5.1 Influence of the identification steps

Because of the non-linearity of the DWC distillation process, the sign and the size of the steps used for the process identification have been found to have a very large influence on the process identification and on the DMC derived from this identification.

For the separation described in 4.11.1 of a mixture with α=(4.65:2.15:1) into 0.99 pure products at optimal operating conditions, an analysis of the influence of the size and sign of the identification steps has been done. "DB" is the considered inventory control, and the considered manipulated variables for composition control are L, V, and S. Four different $\boldsymbol{B_n}$ matrixes are built. To obtain the identification profiles of these four $\boldsymbol{B_n}$, step changes of +0.00001, +0.0001, -0.0001, and –0.00001 kmol/min have been respectively applied to the manipulated variables.

DMC action with Δt=1, n=600, p=300, m=6, and $k2$=100 has been simulated. When a setpoint change of +0.001 in A purity is applied, the DMC system with the model made with steps of +0.0001 becomes unstable. Contrarily, the DMC system with the model made with steps of –0.0001 is able to control. The same happens for a setpoint change of +0.001 in B purity, and for a setpoint change of +0.001 in C purity. And the same happens for greater setpoint changes. Similarly, for the rejection of a disturbance of +0.033 in z_A, the DMC system with the model made with steps of +0.0001 becomes unstable, and the DMC system with the model made with steps of –0.0001 is able to control. DMC systems with the models made with steps of +0.00001 and –0.00001 are both able to control, as proven for a setpoint change of +0.001 in A purity.

Matrix $\boldsymbol{B_n}$ (and $\boldsymbol{B_p}$) is the only difference between the compared DMC systems. Looking at the different identification profiles used to construct the different $\boldsymbol{B_n}$ matrixes, for +0.0001 identification steps, there are inverse responses in the profiles of S-x_{AD}, L-x_{BS}, V-x_{BS}, and L-x_{CB} pairs. For –0.0001 identification steps, there are inverse responses in the profiles of L-x_{BS}, V-x_{BS}, and S-x_{CB} pairs. To see what is the influence of these inverse responses on DMC performance, inverse responses have been removed from the identification profiles. Simulations have shown that the DMC system with the model made with steps of +0.0001 remains unable to control. Therefore, inverse responses in the model are not the reason why this DMC system is not able to control.

Steady state values of the identification profiles are the reason why DMC is not able to control for some identification steps. Looking at these steady state values for different identification steps, it is seen that the identification profiles that depend more on the identification steps are those of L-x_{BS} and V-x_{BS}. In Figures 5.2 and 5.3, these profiles are shown for the four different identification steps (-0.0001, -0.00001, +0.00001, +0.0001 kmol/min).

Different identification profiles can be seen for the different identification steps. The models based on them give DMC which are able to control in some cases (-0.0001, +0.00001, -0.00001) and are not in the other case (+0.0001). Why these identification differences have such a consequence? If the identification is done with steps of +0.0001, the model knowledge is that when L increases the same amount than V, x_{BS} decreases. But in the linear area (steps of ±0.00001), when L increases the same amount than V, x_{BS} increases. This is also the knowledge that has the identification made with –0.0001.

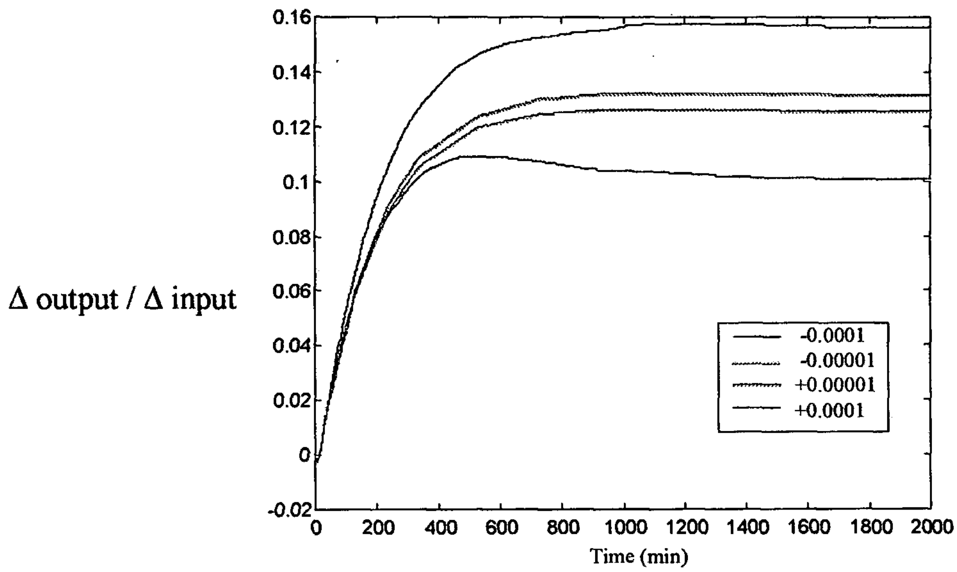

Figure 5.2: Identification profiles of L-x_{BS} pair

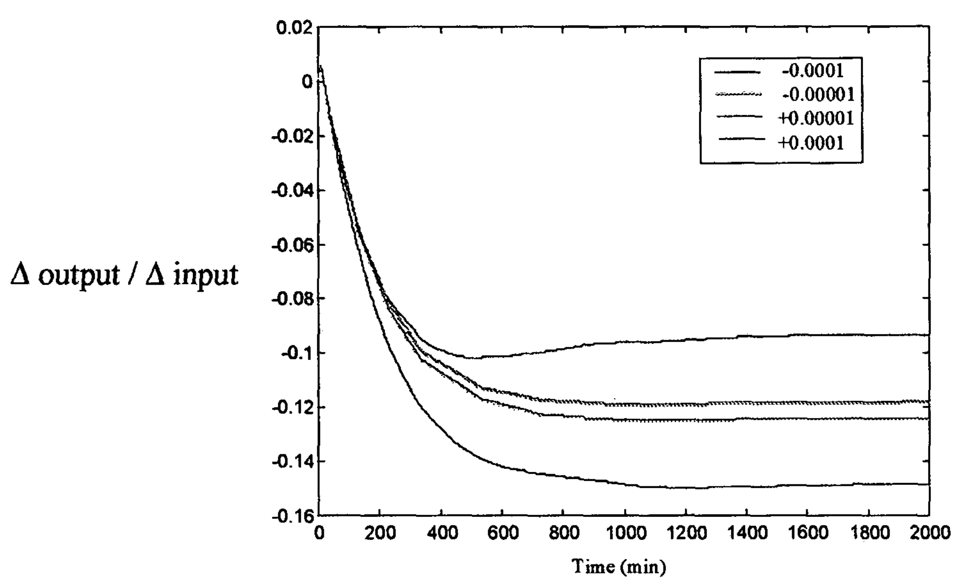

Figure 5.3: Identification profiles of V-x_{BS} pair

It is reasonable to think that the gain signs are the same in the linear area of different operating points. In this case, identification has to be done in the linear area (with small identification steps). It is clear that the operation will cross the linear area before getting the steady state. In this area, a DMC system with a model with right gain signs will converge while a DMC system with a model with wrong gain signs will not be able to control.

If identification is done in the linear area, what happens for large input changes with steady state gain signs different to those in the linear area? In this case, the steady state predicted behaviour is wrong but the first predicted steps are right. As can be seen in Figures 5.2 and 5.3, initial responses of the large and small input changes are very similar. Although the steady state response of x_{BS} to steps of +0.0001 and –0.0001 kmol/min in L and V has different sign, the initial response has the same sign. Since a control action is imposed every Δt, only the initial response at every control action occurs. Because of that, a wrong steady state prediction has no effect and identification within the linear gives a good control.

In order to analyse a second example, the separation described in 4.4 of a mixture with α=(4.65:2.15:1) into products of 0.9895, 0.9709, 0.9815 purity at optimal operating conditions is chosen. With Δt=1, n=600, p=300, m=6, $k2$=100, DMC system with the model made with identification steps of –0.0001 and +0.0001 kmol/min, is able to control. However, for identification steps of –0.001 and +0.001 kmol/min, only the DMC with the model made with negative steps is able to control. Therefore, in accordance to the results for the first example, small identification steps are required to obtain a good DMC system. Non-linearity is lower and the linear area is larger for this second example due most probably to a lower purity of the products.

As conclusion to this section, the steps used to do the process identification have a large influence on the DMC ability to control. To obtain a good DMC model, identification steps have to be very small. This small size of the steps will make the direct identification of a real plant impossible, requiring identification through a model.

5.5.2 Inverse response

Process identification profiles have shown some inverse responses in the DWC (see Figures 5.2 and 5.3). Inverse responses appear when there is a dominant influence which is slower and in a contrary sense than another faster influence. In a distillation column, there are different time constants. Changes in external flows, which have dominant effects, are associated with the large time constants, whereas the effects of the internal flows are significantly faster (Skogestad, 1997). This may cause inverse responses in distillation columns.

Comparing the two separation examples already considered in this chapter, it has been seen that different DWC separations at optimal operating conditions do not have inverse responses in the same input-output pairs. (The example of lower purity products has inverse responses only in the S-x_{AD} pair). Comparing the two separation examples, it has also been seen that different DWC separations at optimal operating conditions do not even have the same steady state gain signs. (The signs of the examples are not the same for L-x_{BS} and V-x_{BS} pairs).

5.6 DMC tuning in a DWC application

In this section, the separation described in 4.4 of a mixture with α=(4.65:2.15:1) into products of 0.9895, 0.9709, 0.9815 purity at optimal operating conditions is chosen in order to study the DMC tuning in a DWC application. The different proposed tunings are tested for a setpoint change in A purity.

A small Δt is preferred for good control performance. Nowadays, Δt is not limited by the computation time, at least for non-restricted DMC. Δt is limited by the sampling time. In this chapter, it is assumed that 0.5 min are needed for the composition measurements, and $\Delta t=1$ min is considered.

As explained in 5.3.3.2, a value of n such that $n*\Delta t$ covers the settling time of the open-loop system is required. At time 600 min, open-loop responses of the studied system have practically achieved the steady state. Simulations with n=600 and with shorter n have shown that large identification horizons permit quicker responses. However, increasing n from 600 to 1000, the performance improves only slightly, what makes n=600 a reasonable value.

As seen in 5.3.3.3, some authors recommend p such that $p*\Delta t$ covers the time needed by the closed-loop system to approach steady state. However, closed-loop time constants are very large for the studied system (p larger than n would be required!). Other authors state that typical p values are between 20 and 50. With p=30 (Δt=1, n=600, p=30, m=6, $k2$=100), the control response is very oscillating and the time needed to achieve steady state is very large (outputs oscillate around a value different from the steady state value). Increasing p to values of p=300 (Δt=1, n=600, p=300, m=6, $k2$=100) oscillations disappear. However, time constants are even larger. A positive influence of the remaining tuning parameters (m and $k2$) is searched without success. With larger $k2$, oscillations are attenuated but closed-loop time constants increase. With larger m (Δt=1, n=600, p=30, m=20, $k2$=100), closed-loop time constants do not improve and performance becomes very bad. Therefore, a value of p giving non-oscillating responses and reasonable closed-loop time constants is not found.

As explained in 5.3.3.4, some authors recommend m between 1 and 6. Others, m such that $m*\Delta t$ covers the 60% of the time needed by the open-loop system to reach steady state. For the studied example however, this is $m*\Delta t$ around 300 min (m=300!), which is too large. Fixing the sampling interval, the identification horizon, the prediction horizon, and the move suppression factor, the influence of the control horizon is found to be very small when changed into the range from m=3 to m=6. Also considering larger values, the influence of m is found small. Comparing Δt=1, n=600, p=300, m=6, $k2$=100 with Δt=1, n=600, p=300, m=20, $k2$=100, the response of the second tuning is only slightly quicker.

For the studied example, the diagonal elements of $B_p'*B_p$ are between 520 and 740. However, very slow responses are obtained with $k2$=100 and for this reason, values larger than 100 are not considered. DMC behaviour for a setpoint change of +0.001 in A purity is simulated. Tunings with two different $k2$ are compared. They are Δt=1, n=600, p=300, m=6, $k2$=10, and Δt=1, n=600, p=300, m=6, $k2$=100. In Figure 5.4, the output profiles for both tunings are shown. In it, it can be seen that outputs for $k2$=10 tend faster to the setpoints and have more irregular profiles. Irregular profiles indicate poor robustness. To see better this effect, in Figure 5.5, the S profiles for both tunings are shown.

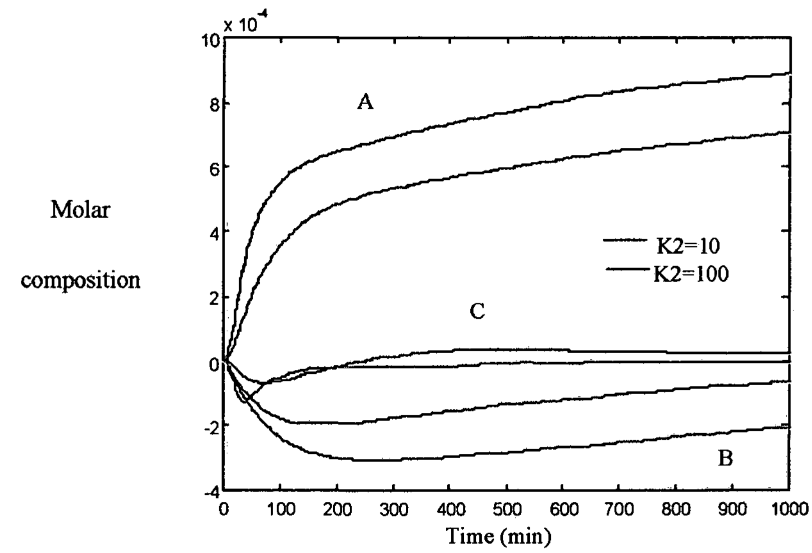

Figure 5.4: Output profiles for a setpoint change in A purity

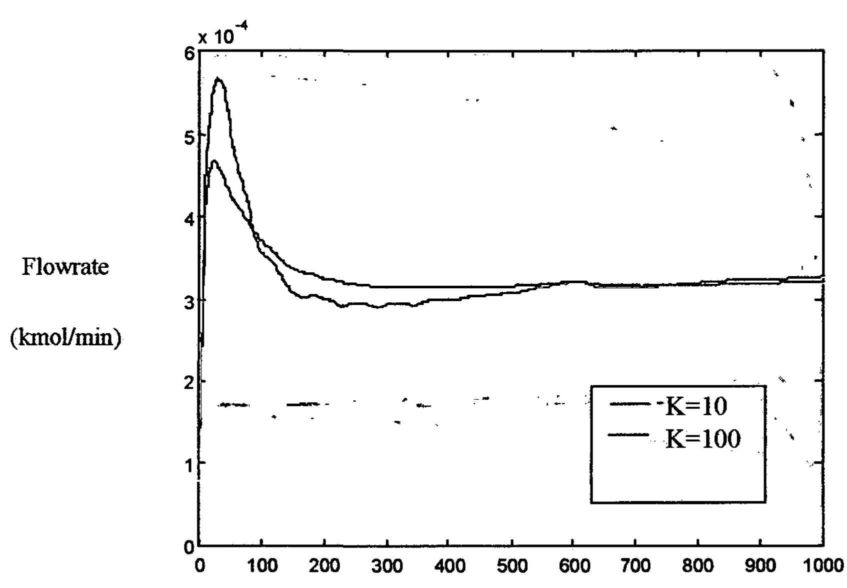

Figure 5.5: S profile for a setpoint change in A purity

In this section, it has been seen that the DMC has a great difficulty to reduce closed-loop time constants. The influence of the tuning parameters on the closed-loop time constants is weak.

5.7 Tuning of a "linear DWC"

In this section, DMC performance for the control of a DWC linear model is studied in order to compare it to the DMC performance for the control of the considered DWC non-linear model. If the tuning appropriate for the DWC linear model gave good performance for the DWC non-linear model, this would indicate robustness of the control system.

The used DWC linear model is a transfer function of order one. Every *G*(*s*) element has the form $K/(\tau_p*s+1)$. Gains and time constants are taken from the non-linear model. The same separation example of the previous section, described in 4.4, is chosen for the comparison.

As can be seen in Figures 5.6 and 5.7 for a setpoint change of +0.001 in A purity, the tuning $\Delta t=1$, $n=600$, $p=100$, $m=3$, $k2=1$ gives nice performance for the DWC linear model and a much worse performance for the DWC non-linear model. In Figure 5.6, it is seen that the non-linear model requires much larger increments in *L* and *V*. But another important difference is that the profiles for the non-linear system are very irregular, indicating poor robustness. This is well appreciated in Figure 5.8, where the *S* manipulated variable is plotted again in a more appropriate scale. Since the tuning of the DWC linear model does not give good performance for the non-linear model, robustness problems are expected.

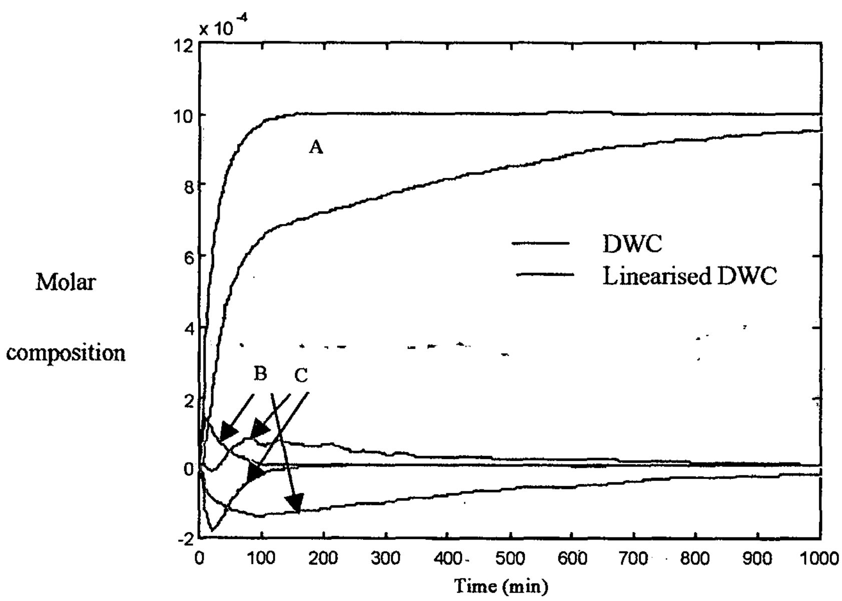

Figure 5.6: Output profiles for a setpoint change in A purity

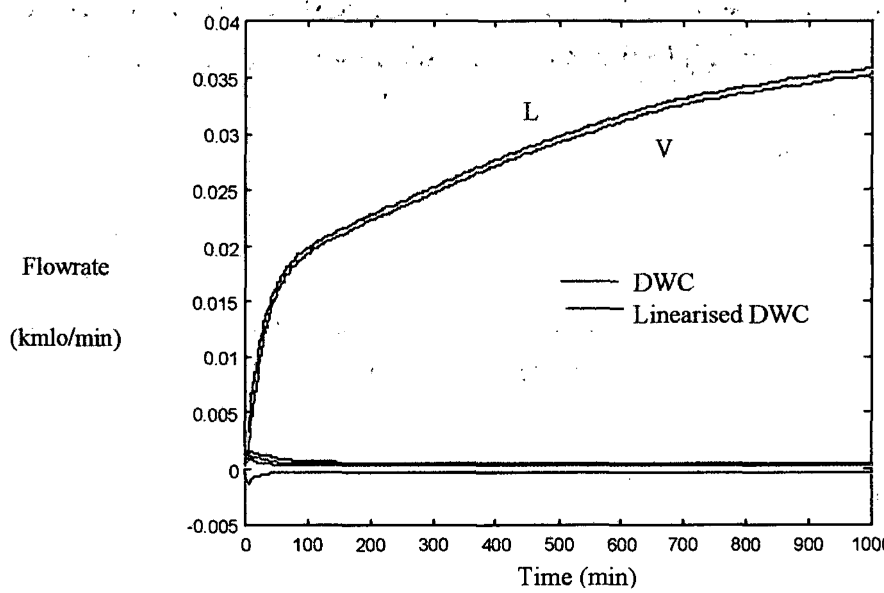

Figure 5.7: Input profiles for a setpoint change in A purity

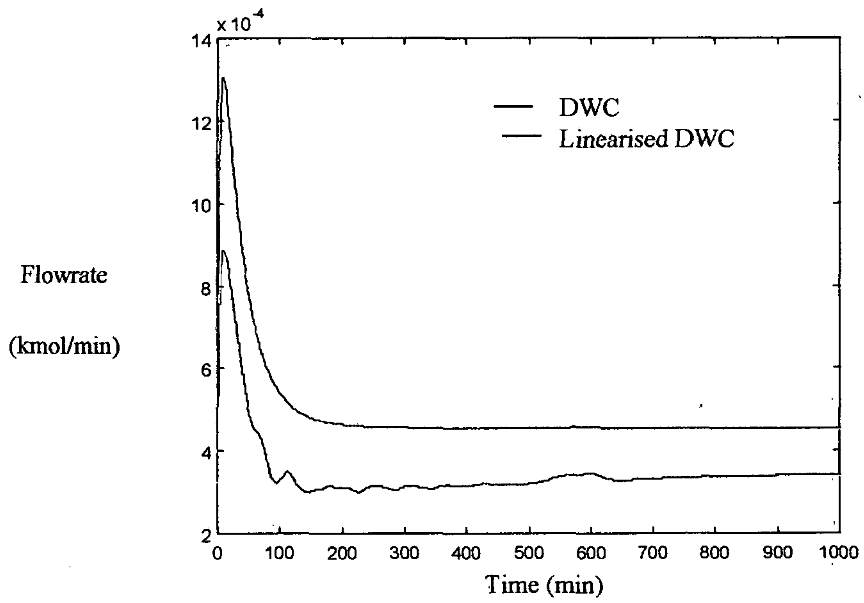

Figure 5.8: *S* profile for a setpint change in A purity

5.8 DMC for a DWC with "LV" inventory control

In the previous chapter, the control structure consisting in "LV" inventory control and *D S B* composition control was found to have a lot of advantages for decentralised feedback control. In this section, a DMC with this control structure is studied.

There is a major problem in the application of DMC to a "LV" stabilised DWC. The problem appears at the early stage of process identification because the steady state gain is singular (see section 4.6). The identification profiles do not get the steady state and final responses do not exist.

The control structure is studied through the separation example described in section 4.11.1 of a mixture with α=(4.65:2.15:1) into 0.99 pure products at optimal operating conditions. With "LV" *D S B* control structure, disturbances make the DMC system unstable. With a disturbance of 0.033 in z_A and tuning Δt=1, n=600, p=600, m=6, $k2$=100, the system becomes unstable. It also does with a disturbance of 0.022 in z_B and with a disturbance of 0.011 in z_A. Even with m=1, the system becomes unstable. A disturbance in z_A of 0.033 makes the control system unstable even with Δt=1, n=1000, p=1000, m=6, $k2$=100 and Δt=1, n=800, p=800, m=1, $k2$=100. On the other hand, no tuning has been found able to achieve a setpoint change of +0.001 in the A purity.

Normally, large n and p are required for conservative control. However, to exclude the effect of the open-loop divergence from the prediction profiles, tunings with smaller n and p parameters are tested. Results are that for large parameters, the control system becomes unstable and for small parameters, the performance is unacceptable.

For the second separation example (described in section 4.4), some disturbances can be rejected and some setpoint changes achieved. However, control performances are very bad.

It can be concluded that DMC of "LV" stabilised DWC with *D S B* composition control structure is not appropriate. Large n and p parameters are required for conservative control, but profiles with large n and p capture the divergence of the open-loop system and the control becomes unstable.

5.9 Comparison between decentralised feedback and DMC strategies

As was seen in the introduction of this chapter, DMC is a control strategy more sophisticated than diagonal feedback control. However, it is not clear which of the two strategies will be better for the control of the DWC.

DMC depends on the DWC model, which is linear. In section 5.5, the important consequences of the DWC non-linearity due to a linear identification were seen. In section 5.7, it was seen that the DMC of a DWC linear model differs severely to the DMC of a DWC non-linear model.

In the previous section, it has been concluded that one of the more performing control structures with decentralised feedback control, "LV" *D S B*, can not be implemented with DMC. In this sense, decentralised feedback control is less restrictive because it can be applied to a system with singular steady state matrix gain.

DMC takes into account the effect of all the inputs over every output. Diagonal feedback control does not take interactions into account. However, some times, the interactions favour the rejection of disturbances. Relative Disturbance Gain (***RDG***) is an indicator of the natural tendency of a system to favour the rejection of disturbances with the interactions. If this natural ability exists, decoupling is not desired and PI is preferred to DMC. Therefore, ***RDG*** may be a useful tool to select the appropriate control strategy.

Decentralised feedback control is not inherently discrete as DMC is. For some measured variables, the decentralised feedback control can be implemented in a continuous manner. For other measured variables, it is implemented in a discrete manner. For instance, temperature measurements can be done continuously and continuous feedback is possible. On the other hand, compositions can not be measured continuously and discrete feedback is needed. To properly compare the two control strategies, discrete PI controllers are considered. Since the Δt limiting restriction is the time needed to measure, which affects equally both strategies, the same Δt (Δt=1 min) is applied to both control strategies.

The appropriate tuning for setpoint tracking and disturbance rejection can be quite different. In fact, even the appropriate tuning for every setpoint change and every disturbance may differ. In the following sections, comparisons between the DMC and the decentralised feedback control strategies are done separately for different disturbances and setpoint changes.

5.9.1 Case study 1

The separation chosen as case study 1 is the separation described in 4.11.1 of a mixture with α=(4.65:2.15:1) into products of 0.99 purity at optimal operating conditions. The DWC design is the optimal design obtained with *RR*/*MRR*=2, according to the methodology in section 2.6.2. The chosen control structure consists in "DB" inventory control and *L S V* composition control. As was seen in 4.11.1, this is the best control structure in terms of *MRI*, *CN* and ***RGA***. At *s*=0.04, *MRI*=0.25 and *CN*=91. Steady state and *s*=0.04 ***RGA*** are shown in equations 5.2 and 5.3. These *MRI*, *CN* and ***RGA*** indicate quite extreme conditions because *CN* and ***RGA*** values are high. In 5.9.2, a case study with better controllability indexes will be studied.

$$\boldsymbol{RGA}(0.04) = \begin{pmatrix} 7.47 & 0.0007 & 7.19 \\ 2.45 & 0.82 & 2.47 \\ 9.34 & 0.19 & 9.39 \end{pmatrix} \qquad (5.2)$$

$$\boldsymbol{RGA}(0) = \begin{pmatrix} 67.64 & 0.01 & 66.65 \\ 15.16 & 0.24 & 14.41 \\ 81.80 & 0.74 & 82.06 \end{pmatrix} \qquad (5.3)$$

5.9.1.1 Setpoint tracking

Setpoint change in A purity

With Δt=1, n=600, p=300, m=6, $k2$=100, a setpoint change of +0.001 in A purity is loaded. DMC response can be seen in Figures 5.9 to 5.12. Figures 5.9 and 5.10 show the output profiles and Figures 5.11 and 5.12 show the input profiles. It can be seen that the steady state achievement is extremely slow.

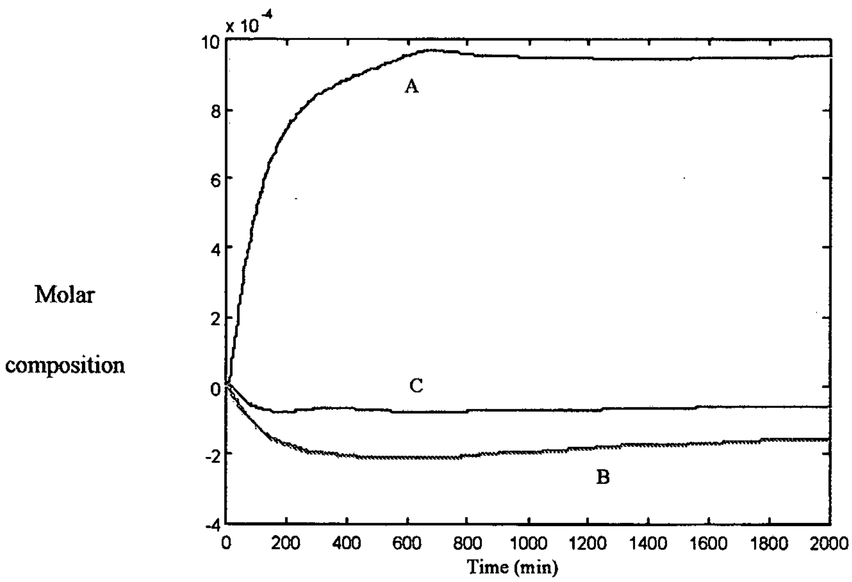

Figure 5.9: Output profiles with a setpoint change in A purity

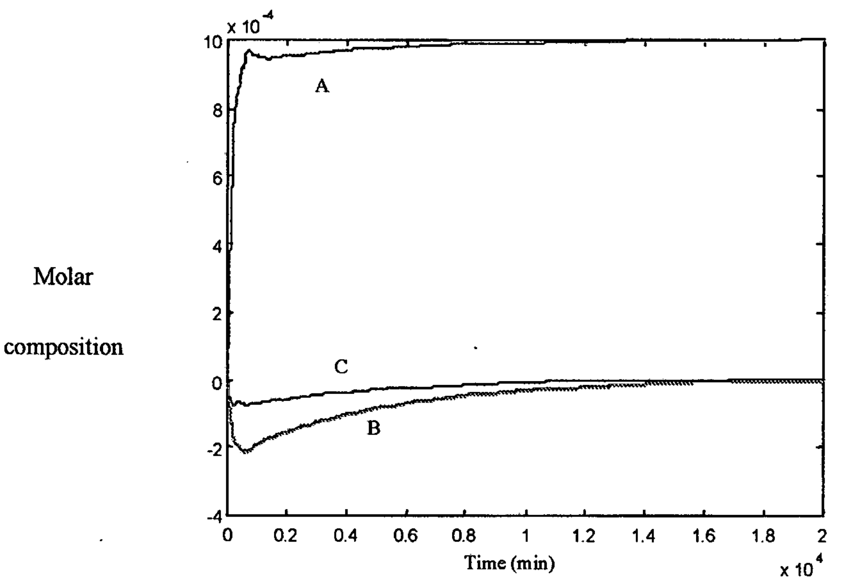

Figure 5.10: Output profiles with a setpoint change in A purity

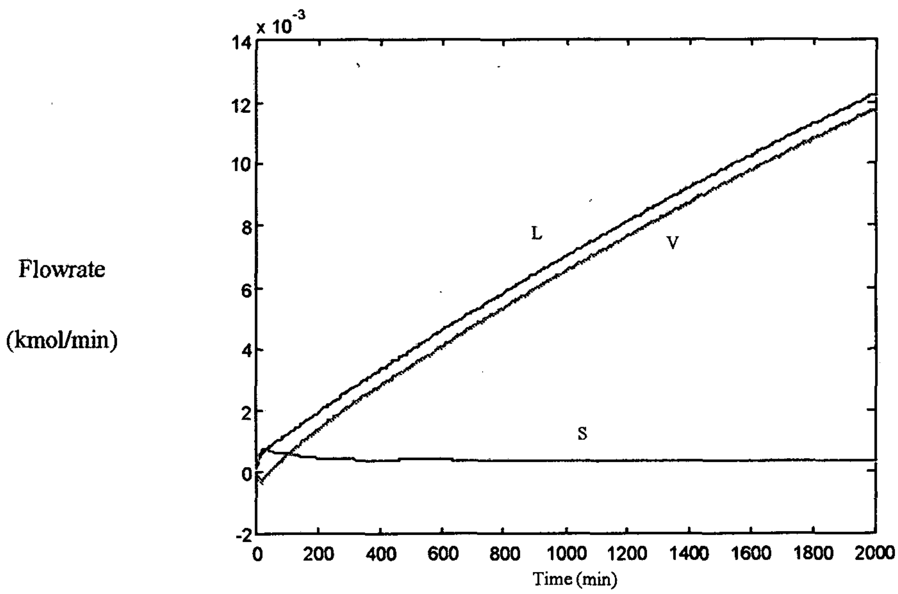

Figure 5.11: Input profiles with a setpoint change in A purity

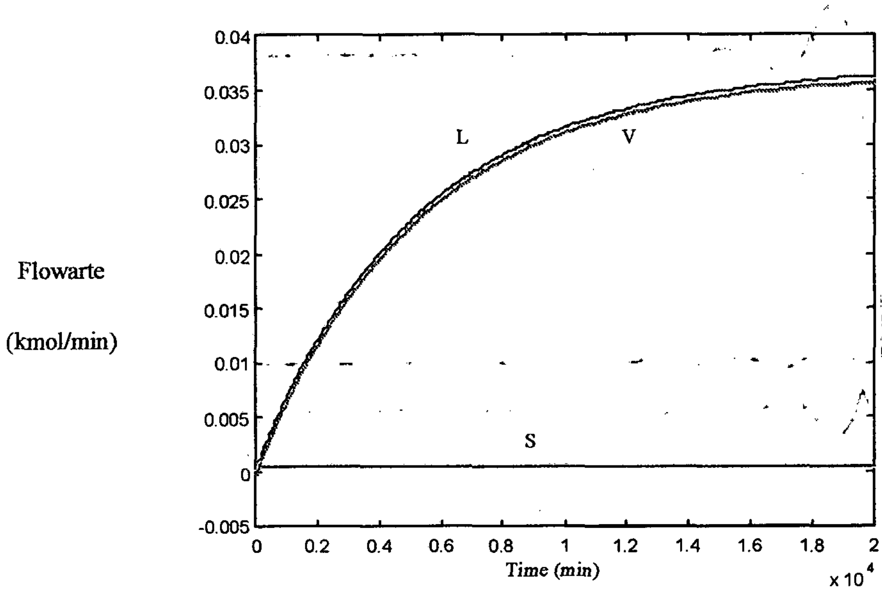

Figure 5.12: Input profiles with a setpoint change in A purity

Since the DMC performance is not satisfactory, a better tuning is searched. With the same tuning (Δt=1, n=600, p=300, m=6, $k2$=100) but Δt=0.5, the steady state achievement is two times faster and deviation of B and C compositions is slightly smaller. However, it is nonsense to make the sampling period smaller because this would not be possible in real conditions.

With the same tuning (Δt=1, n=600, p=300, m=6, $k2$=100) but $k2$=50, the steady state achievement is also faster (at minute 2000, L and V are 0.017 kmol/min). However, deviation of B and C compositions increases. With $k2$=10, convergence is still faster (at minute 2000, L and V are 0.026 kmol/min), but the shape of the input profiles (specially S) is quite irregular, indicating poor robustness. With $k2$=1, setpoints are not achieved at minute 500, and the profiles are very irregular (even with m=3 and m=2). Finally, with $k2$=0.1, setpoints are not yet achieved at minute 500.

Different move suppression factors to the different inputs are implemented. Since S is the first input to have irregular profiles, a larger lambda is given to it. However, between Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=10, $\lambda(2,2)$=10, $\lambda(3,3)$=100 and Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=10, $\lambda(2,2)$=10, $\lambda(3,3)$=10, very small differences have been found.

As can be seen in Figure 5.13, with a smaller p (Δt=1, n=600, p=50, m=6, $k2$=100), a shorter settling time is got. However, the achievement of steady state is equally long. The problem of long time constants can not be improved changing p.

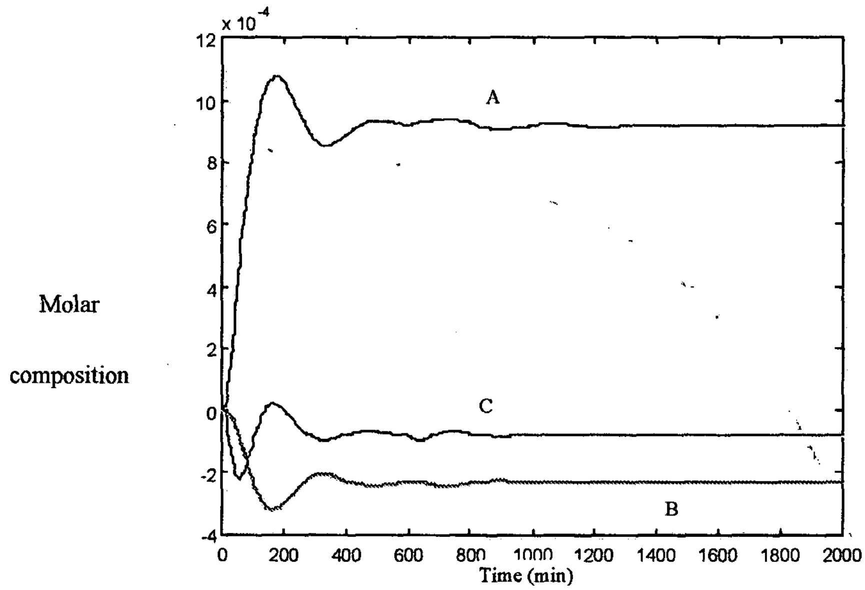

Figure 5.13: Output profiles for a setpoint change in A purity

Finally, the m parameter has a very small influence in the response of the DMC, at least when it is varied between 3 and 6. DMC performance with Δt=1, n=600, p=300, m=3, $k2$=100 and Δt=1, n=600, p=300, m=6, $k2$=100 is very similar.

Therefore, as was found for the example in 5.6, the time needed by DMC to achieve steady state is very long. For all the proposed tunings, a common characteristic is found: L and V increase very slowly and with similar ratios.

To compare the performance of DMC with the performance of diagonal feedback control for the setpoint tracking of A purity, the performance of PI controllers is simulated. With a tuning of K_c=0.32, τ_c=26.67 (loop L-x_{AD}), K_c=-0.30, τ_c=66.67 (loop S-x_{BS}), and K_c=0.28, τ_c=31.11.(loop V-x_{CB}), results shown in Figures 5.14 and 5.15 are obtained. In them, it can be seen that all three setpoints are achieved at minute 500, which is much faster than with the DMC. On the other hand, the deviation in C composition is about three times the deviation encountered with the DMC. PI tunings able to reduce the deviation in C composition are searched, but they are not found. With half K_c and double τ_c in the three control loops, convergence is slower but deviation in C composition is almost the same. With constant K_c and double τ_c in the three control loops, convergence is slower and the deviation in C composition only a little smaller.

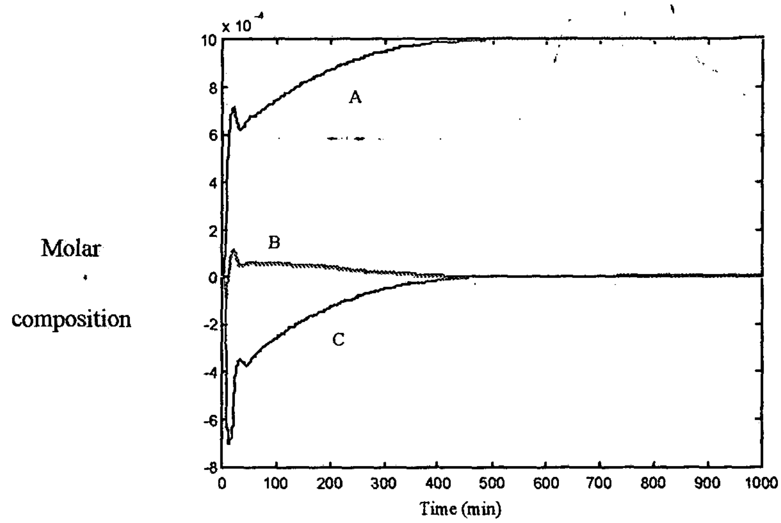

Figure 5.14: PI output profiles for a setpoint change in A purity

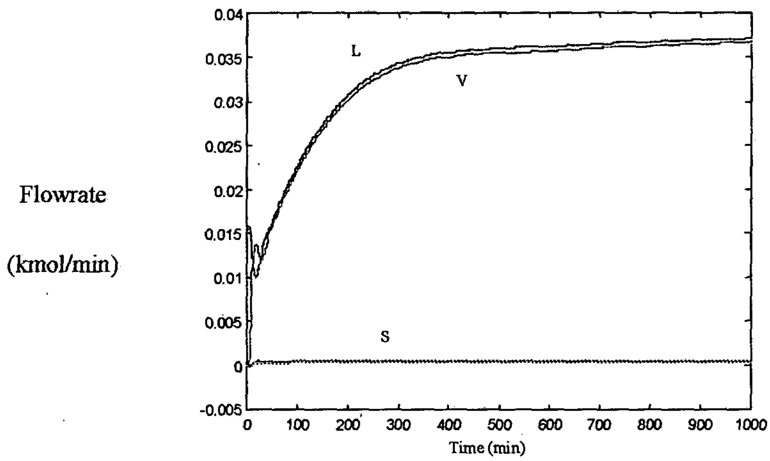

Figure 5.15: PI input profiles for a setpoint change in A purity

According to the stability criterion described in 4.9.1, with the tuning corresponding to Figures 5.14 and 5.15, robust stability for uncertainty in input channels is found (*wi* for 20% gain error and neglected time delay of 0.9 min). In Figure 5.16, it is seen that max(σ($wi*T_I$)) is close to 1.

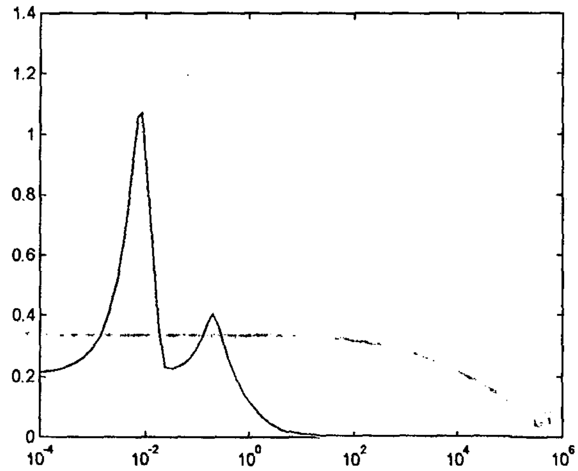

Figure 5.16: max(σ ($wi*T_I$))

Resuming, for setpoint tracking of A purity, diagonal feedback control has shorter closed-loop time constants than the DMC, and PI tuning parameters have larger influence on the control performance. However, the diagonal feedback control is not able to eliminate the deviation of C composition, which is three times the deviation for the DMC.

Setpoint change in B purity

A setpoint change in B purity has been loaded to the DMC control system with Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=28, $\lambda(2,2)$=28, $\lambda(3,3)$=60. Simulation results are shown in Figures 5.17, 5.18, and 5.19. As found for a setpoint change in A purity, the time needed to achieve steady state is very long. (This time is still longer with Δt=1, n=600, p=300, m=6, $k2$=100). Changing individual move suppression factors, it has been observed that the move suppression factor of input S, ($\lambda(3,3)$, does not affect the time needed to achieve steady state. Reducing the move suppression factors of L and V inputs, faster responses are achieved. However, the control is not much faster when profiles become irregular. A satisfactory tuning that reduces the time needed to achieve steady state is not found.

The feedback control response to the same setpoint change is shown in Figures 5.20 and 5.21. Tuning of the PI controllers is the same considered for a setpoint change in A purity. As for a setpoint change in A purity, simulations show that steady state is achieved much faster with the

PI controllers than with the DMC. However, PI controllers present larger deviation in the output variables.

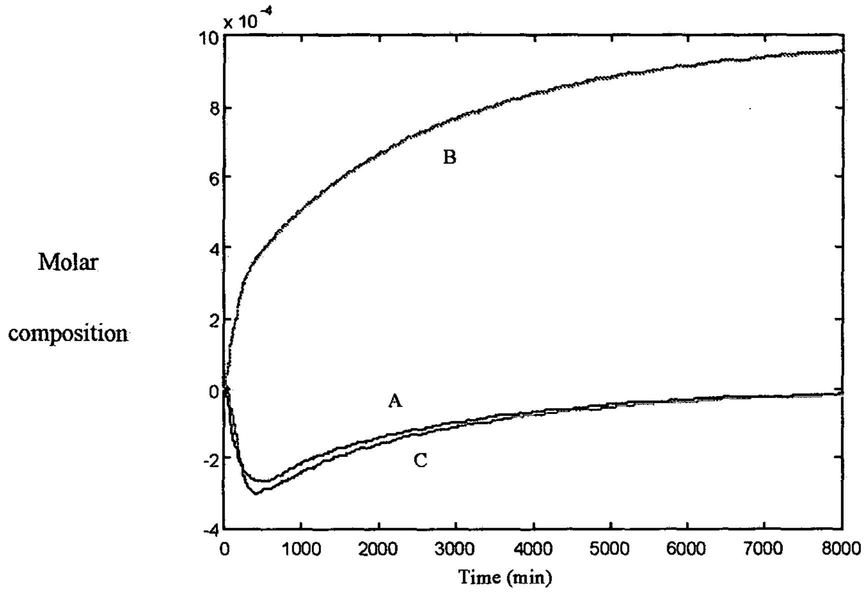

Figure 5.17: Output profiles for a setpoint change in B purity

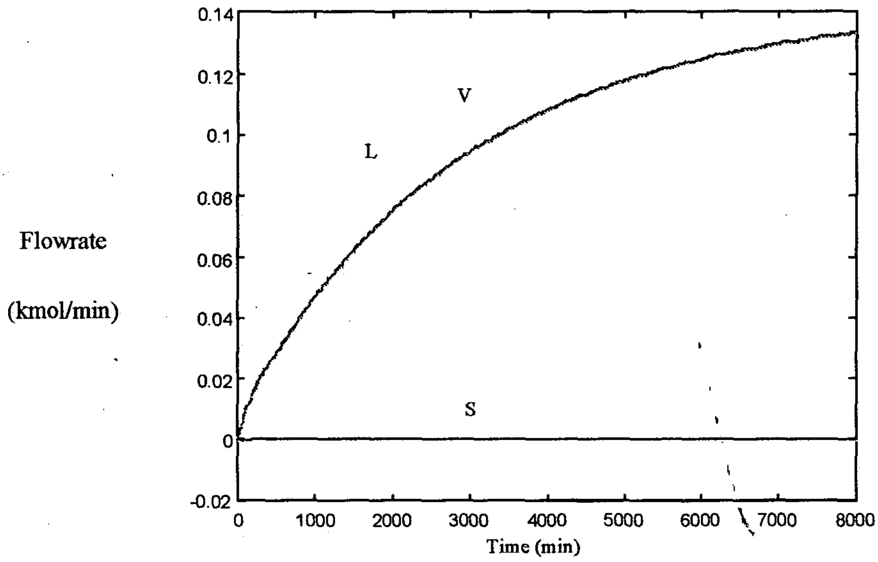

Figure 5.18: Input profiles for a setpoint change in B purity

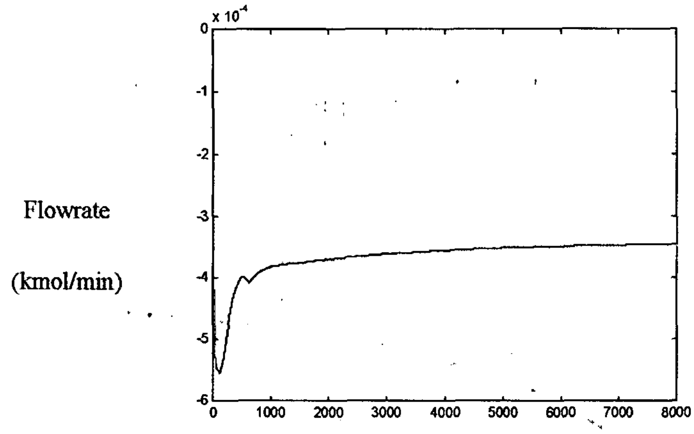

Figure 5.19: S manipulated variable profile for a setpoint change in B purity

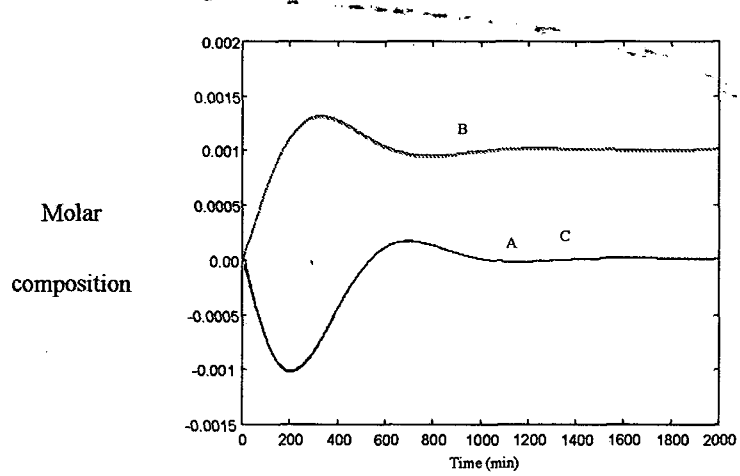

Figure 5.20: PI output profiles for a setpoint change in B purity

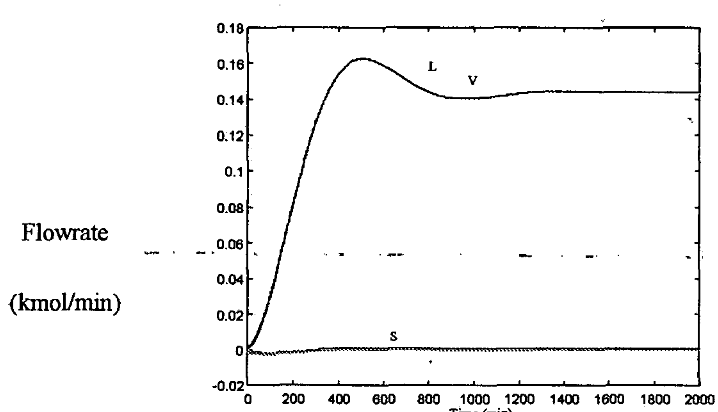

Figure 5.21: PI input profiles for a setpoint change in B purity

Setpoint change in C purity

Loading a setpoint change in C purity, it has also been found that the achievement of the steady state is very slow with DMC, and its tuning parameters have a weak influence on the control performance.

Discussion and conclusions

For setpoint tracking of the three controlled variables, DMC presents the problem of very large closed-loop time constants. Even for setpoint changes of –0.05, this problem is got. This occurs because L and V increase with similar ratios in order to move A and C purity in the same direction.

DMC certainly uses the information of what is the influence of L, V and S over all the outputs when L, V and S play alone. For instance, what is the response to a change in L when V and S are constant. But DMC does not have the information of how the inputs play at the same time, and assumes linearity. In a DWC with "DB" stabilisation, when L changes with constant S and V, B and D also change in order to stabilise the column, affecting the products composition. Specifically, if L increases with V and S constant, B increases and D decreases. As a result, C purity decreases and A purity increases. However, when L and V change both at the same time, D and B remain almost unchanged and the purity of products is only affected by the change of the internal variables L and V (and not by the change of the external variables D and B). In this case, much larger changes in L are needed to increase the A purity. From the process identification, the behaviour changing external variables is captured, which corresponds to much larger gains. Therefore, although DMC has more information about the process, this information is erroneous in some situations, what makes DMC not always better for non-linear systems. In this section for example, it has been found that DMC has much longer closed-loop time constants than the PI controllers, and DMC tuning parameters have a small influence on the control performance. PI controllers can be tuned more tightly without robustness problems.

5.9.1.2 Disturbance rejection

In this section, disturbances of +10% of the nominal values are considered. Such disturbances cause movements in the output variables much larger than the movements considered when studying setpoint changes in the previous section. Therefore, the operating conditions are farther from the nominal conditions.

Disturbance in z_A

In Figures 5.22 and 5.23, the response profiles of a DMC system controlling a disturbance in z_A are shown. The DMC tuning is Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=14, $\lambda(2,2)$=14, $\lambda(3,3)$=60. (With Δt=1, n=600, p=300, m=6,$k2$=100, overshoots were larger). Reducing the move suppression factors, the overshoots can be reduced. However, profiles are very irregular for $\lambda(1,1)$=5, $\lambda(2,2)$=5, $\lambda(3,3)$=60, for which the peak of C composition is still –0.0075.

In the output profiles, two zones can be distinguished. In the first one (time<1000 min), the outputs move much faster than in the second one (time>1000 min). In the first one, A and C compositions move in opposite directions and in the second one, they move in the same direction. Looking at the input profiles in Figure 5.23, it can be seen that in the second zone, L and V decrease with similar ratios. Therefore, the problem of long closed-loop time constants is not a problem of setpoint tracking, but a problem that appears whenever L and V increase or decrease with similar ratios to make A and C compositions move in the same direction.

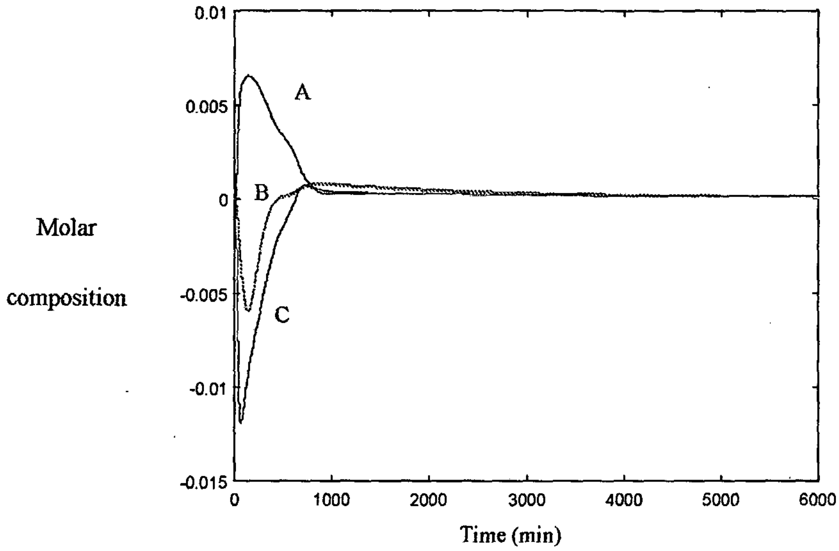

Figure 5.22: Output profiles for a disturbance in z_A

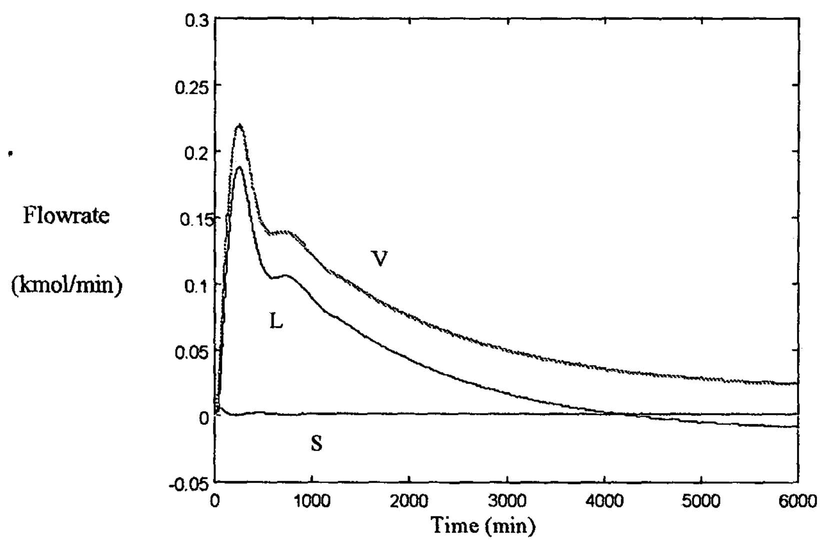

Figure 5.23: Input profiles for a disturbance in z_A

Feedback control behaviour for the rejection of a disturbance of +0.033 in z_A has also been simulated. The tuning of the PI controllers is the same considered for a setpoint change in A purity. Results are shown in Figures 5.24 and 5.25. Interestingly, the overshoots in the output variables are much smaller than those obtained with DMC (compare Figures 5.22 and 5.24). Also, the manipulated variables have changed into a smaller range (compare Figures 5.23 and 5.25). Contrarily at what happened for setpoint changes, for z_A disturbance rejection, the variation of the output variables is larger with DMC than with the PI controllers. Closed-loop time constants are larger for the DMC. Therefore, diagonal feedback control performance is better from both points of view.

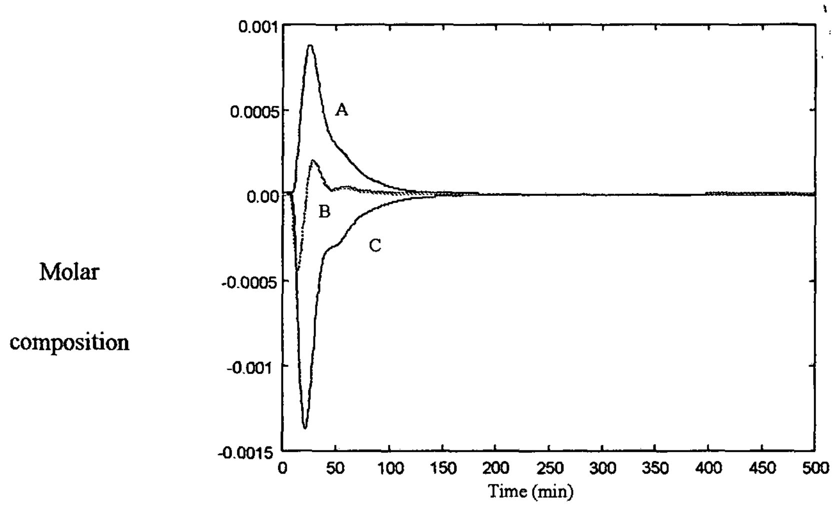

Figure 5.24: PI output profiles for a disturbance in z_A

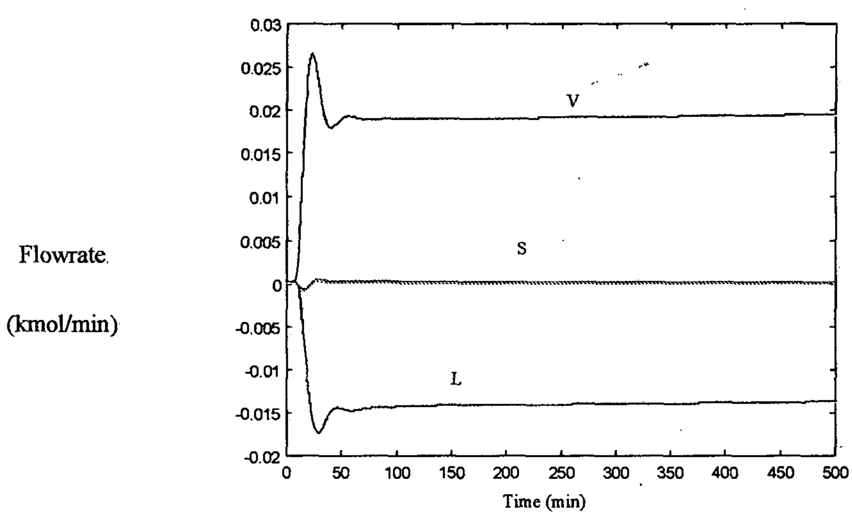

Figure 5.25: PI input profiles for a disturbance in z_A

Disturbance z_B

For a disturbance rejection of +0.033 in z_B and tuning Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=14, $\lambda(2,2)$=14, $\lambda(3,3)$=60, the DMC behaviour is simulated. Results are shown in Figures 5.26 and 5.27. (With Δt=1, n=600, p=300, m=6, $k2$=100, overshoot in output variables was larger).

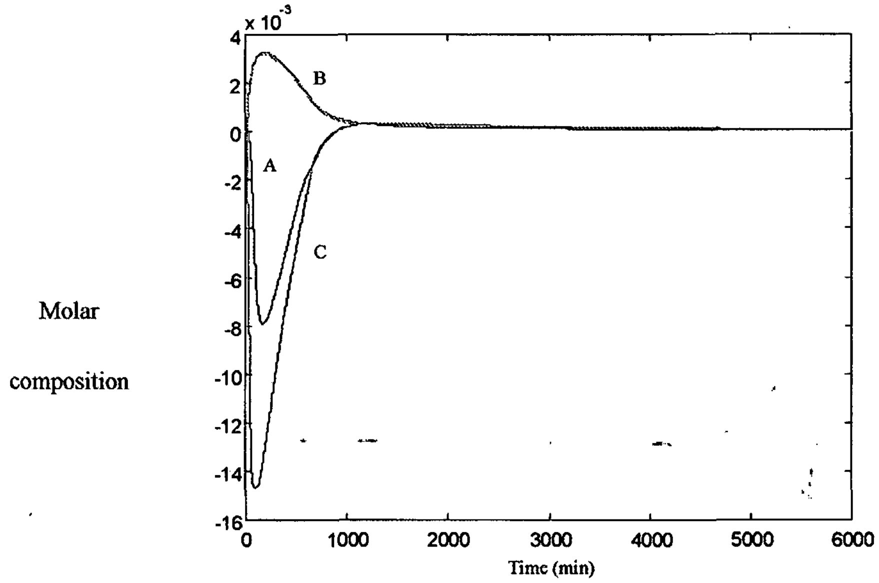

Figure 5.26: Output profiles for a disturbance in z_B

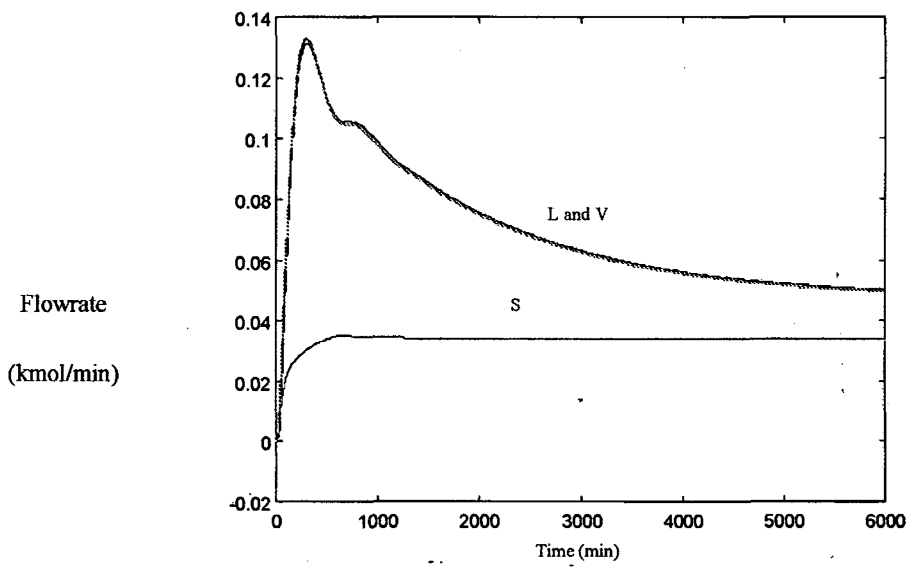

Figure 5.27: Input profiles for a disturbance in z_B

In Figures 5.28 and 5.29, feedback control behaviour for the rejection of a disturbance in z_B is shown. The tuning is K_c=0.32, τ_c=26.67 (loop L-x_{AD}), K_c=-1.21, τ_c=80.66 (loop S-x_{BS}), K_c=0.28, τ_c=31.11 (loop V-x_{CB}). For this tuning, the peak of σ ($wi*T_I$) is 0.6, indicating robust stability. Comparing Figures 5.26 and 5.28, it is seen that the overshoot in C composition is almost 3 times larger for DMC strategy. Besides, more time is needed by DMC to achieve steady state. These results are similar to the results found for a disturbance in z_A, and indicate the superiority of feedback control strategy.

Molar composition

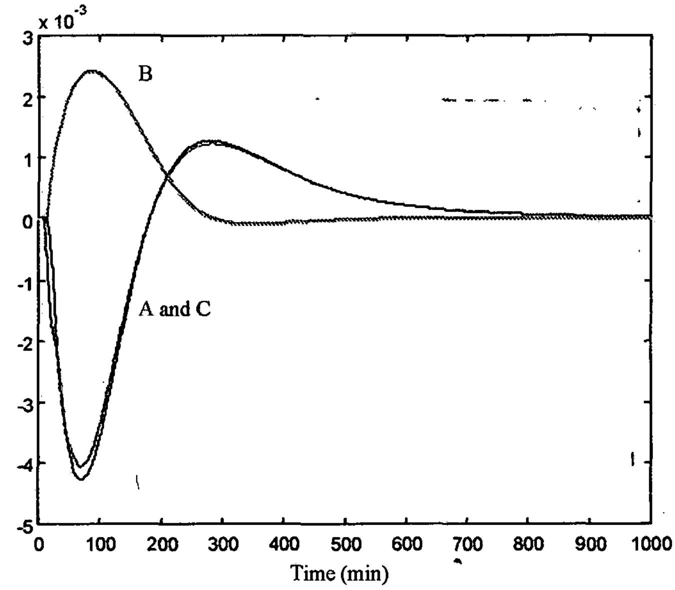

Figure 5.28: PI output profiles for a disturbance in z_B

Flowrate (kmol/min)

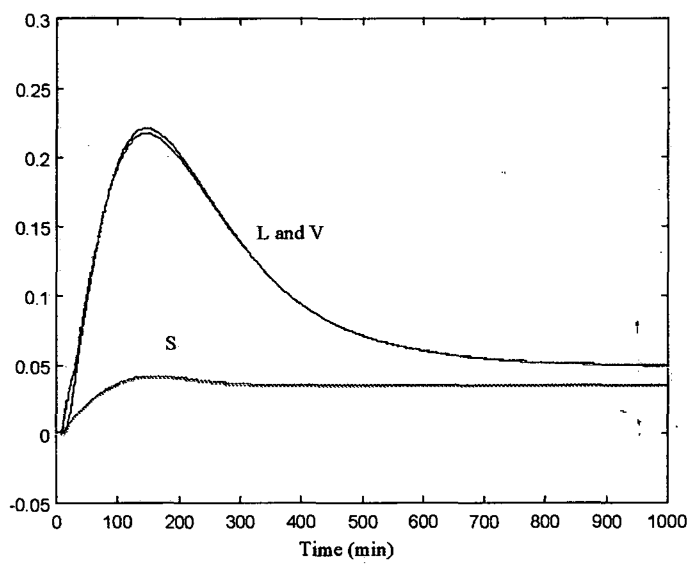

Figure 5.29: PI input profiles for a disturbance in z_B

Feed flowrate disturbance

Finally, for a disturbance in the feed flowrate and Δt=1, n=600, p=300, m=6, $\lambda(1,1)$=14, $\lambda(2,2)$=14, $\lambda(3,3)$=60, the DMC behaviour is simulated. Results are shown in Figures 5.30 and 5.31. With Δt=1, n=600, p=300, m=6, $k2$=100, the overshoot in C purity reached 0.045. This overshoot could be reduced diminishing $k2$. However, with $k2$=20, profiles already became irregular. In this case, the system approaches steady state increasing A and decreasing C, what avoids the problem of large closed-loop time constants.

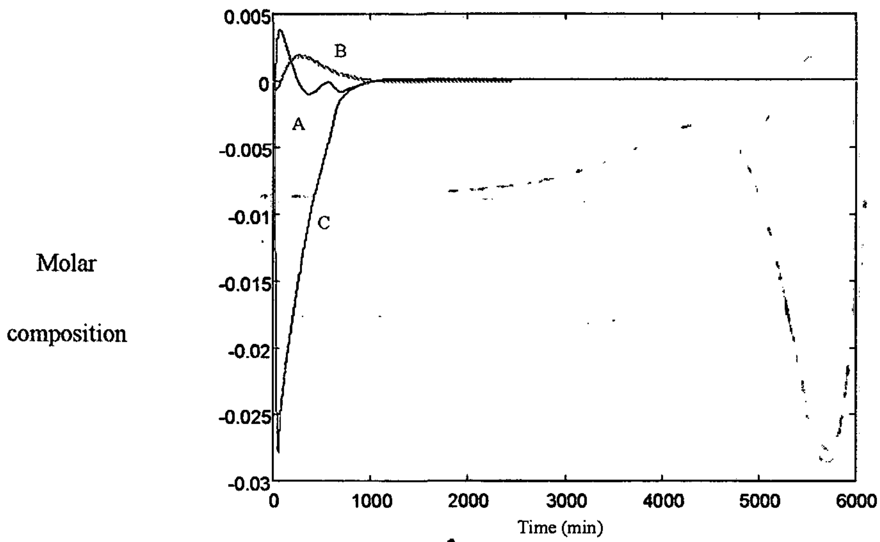

Figure 5.30: Output profiles for a disturbance in F

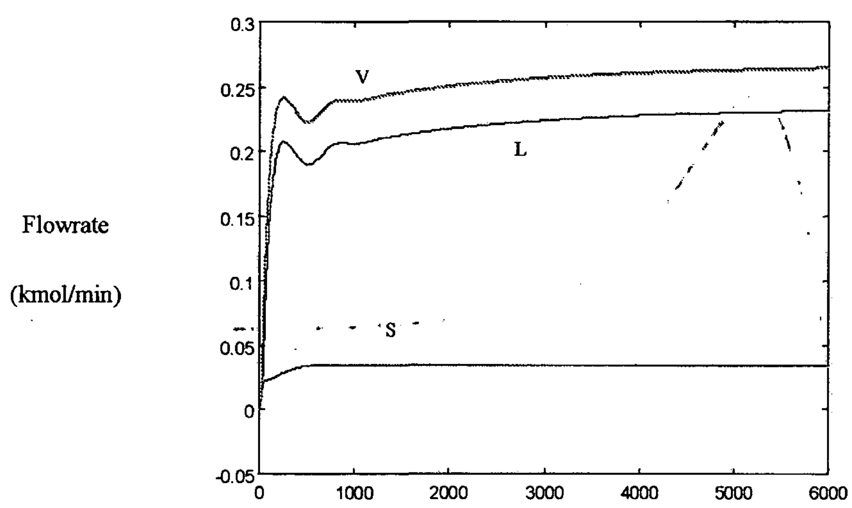

Figure 5.31: Input profiles for a disturbance in F

PI behaviour with the same tuning considered for the rejection of F is simulated. Results are shown in Figures 5.32 and 5.33. As for the other disturbances, overshoots are smaller with the PI controllers than with DMC (see Figures 5.30 and 5.32).

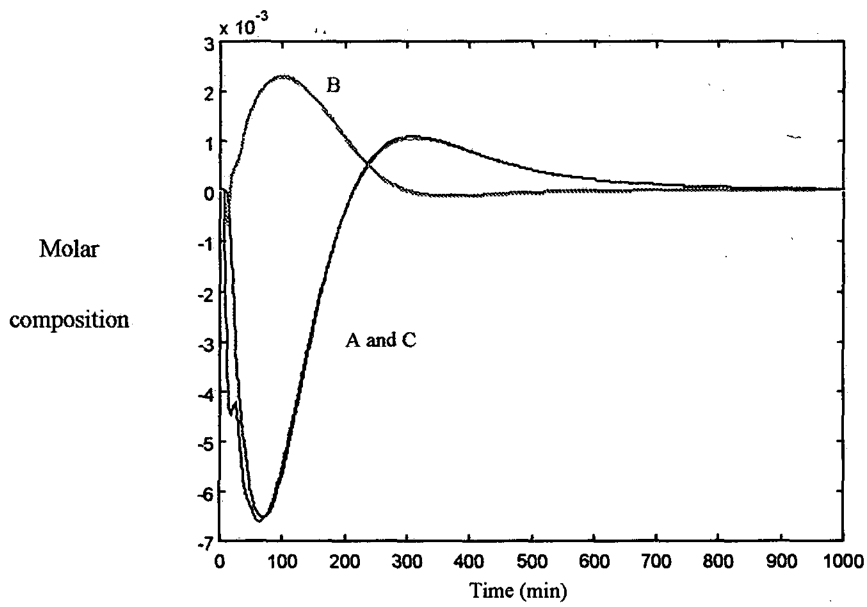

Figure 5.32: PI output profiles for a disturbance in F

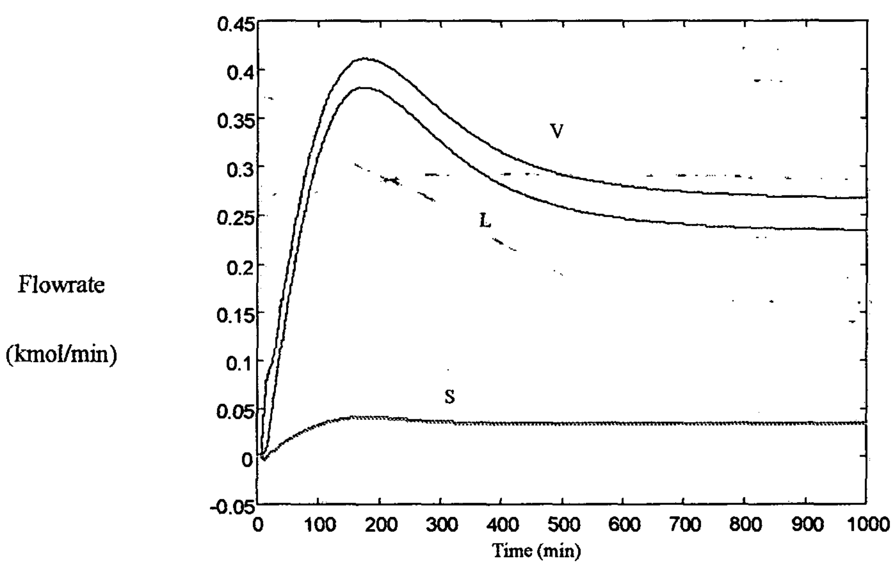

Figure 5.33: PI input profiles for disturbance in F

RDG analysis

As already explained, one of the reasons of the DMC inferiority may be its intention to decouple when it is not desired. The ***RDG*** is useful as a measure of whether or not favourable interaction exists in a decentralised feedback control system (Stanley et al., 1985). The ***RDG*** elements indicate the natural ability of a system to eliminate disturbance effects thanks to the interaction between input variables. ***RDG*** is the closed-loop disturbance gain over the open-loop disturbance gain and is calculated as indicated in equation 5.4, where ./ denotes element-by-element division.

$$\boldsymbol{RDG}(s)=\boldsymbol{CLDG}(s)./\boldsymbol{Gd} \qquad (5.4)$$

A small value of ***RDG*** means that closed-loop disturbance gain is small compared to open-loop disturbance gain, or that interaction makes the effect of disturbances smaller. Specifically, ***RDG*** values smaller than 1 indicate favourable effect of interactions over the disturbance rejection.

In Figures 5.34, 5.35, and 5.36, the ***RDG*** elements for the studied system are plotted. It can be seen that some gains have values larger than one and others have values smaller than one. In general, the rejection of F and z_B are the less favoured by the interactions, and the rejection of q_F is the most favoured. In a plant in what only disturbances in q_F were expected, the decoupling derived of DMC would be negative. However, general conclusions may hardly be derived from the ***RDG*** plots because each ***RDG*** element has a different behaviour.

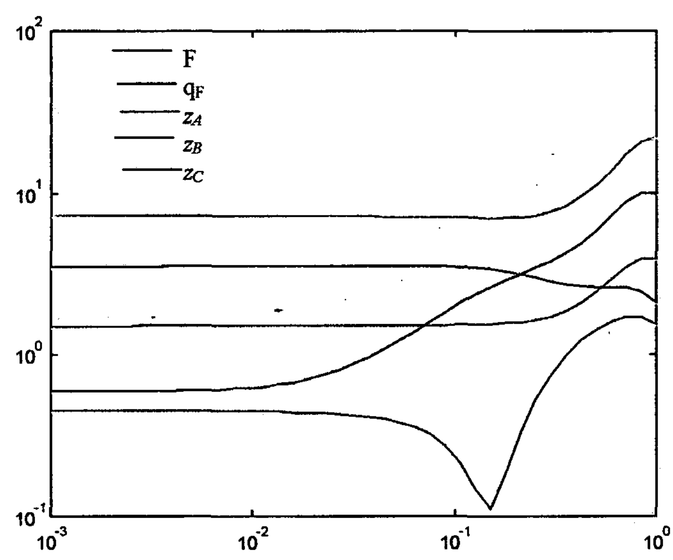

Figure 5.34: ***RDG*** elements for output 1

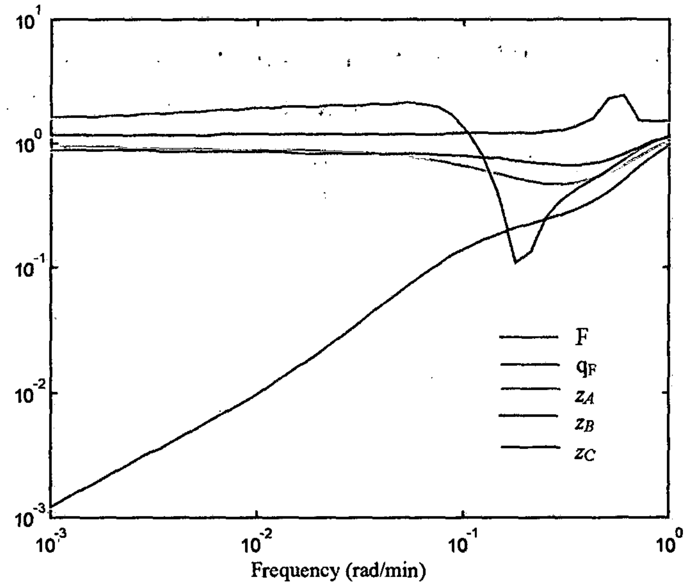

Figure 5.35: ***RDG*** elements for output 2

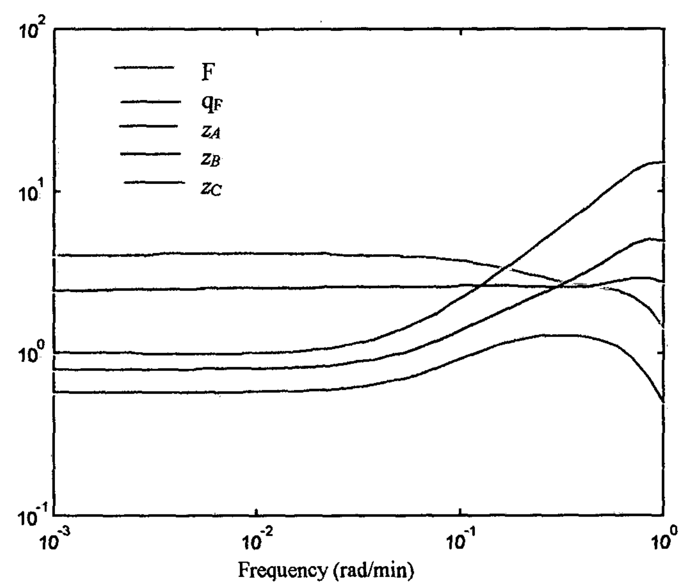

Figure 5.36: ***RDG*** elements for output 3

5.9.1.3 Conclusions

From all the simulations in section 5.9.1, it has been observed that the influence of the DMC tuning parameters over the control performance is weak. Specially, when L and V move with similar ratios in order to increase or decrease A and C purity at the same time, DMC actuates very slowly and feedback control performance is much superior. For setpoint tracking, DMC is able to obtain smaller deviations. For disturbance rejection, PI controllers present smaller overshoots.

The difficulty of the control systems to move A and C purities in the same direction is due to a high directionality. When L and V increase with similar ratios keeping the external flows constant, gains become very small. Both control strategies are affected by this high directionality. However, the problem is much better solved by the diagonal feedback control strategy.

It is interesting to notice that high *CN* is not a problem for DMC. Since DMC contains a linear model of the process, it knows that the gain in one direction is lower than the gain in another direction as well as *CN* expresses it. But the DWC has a difficulty added to the one expressed by the high *CN* because the directionality is increased by the non-linearity. This is due to the difference in gains depending on the change in external flows.

5.9.2 Case study 2

In this section, another case study is analysed in order to compare diagonal feedback control and DMC strategies for the DWC composition control. The same separation considered in previous example is considered: a mixture with α=(4.65:2.15:1) separated into 0.99 molar pure products at optimal operation. What changes in this case is the DWC design. As the design considered in case study 1, the design has been obtained according to the optimisation procedure described in section 2.6.2. However, in this case, the design has been found with *RR/MRR*=1.23. *NT*=58, *NP*=18, *NM*=40, *NS*=21, *NCB*=10, *NCD*=31, and *NF*=9. As was seen in chapter two, DWC is energetically more favourable for large columns (small *RR/MRR*).

The studied control structure is also "DB" stabilisation, and $L\ S\ V$ composition control. For this control structure, at s=0.04, the *MRI*=0.54 and *CN*=25.7. Steady state and s=0.04 ***RGA*** values are indicated in equations 5.5 and 5.6. These *MRI*, *CN*, and ***RGA*** values indicate a better controllability than for case study 1. Chapter seven will address the controllability of the DWC depending on the column design.

$$\boldsymbol{RGA}(0.04) = \begin{pmatrix} 1.93 & 0.001 & 1.18 \\ 1.02 & 0.49 & 1.13 \\ 2.06 & 0.52 & 2.18 \end{pmatrix} \qquad (5.5)$$

$$\boldsymbol{RGA}(0) = \begin{pmatrix} 11.80 & 0.005 & -10.80 \\ 7.55 & 0.22 & -6.77 \\ -18.3 & 0.77 & 18.57 \end{pmatrix} \qquad (5.6)$$

A setpoint change of +0.001 in A purity has been loaded to a DMC system with Δt=1, n=600, p=300, m=6, $k2$=100. In Figures 5.37 and 5.38, simulation results are shown. It can be seen that profiles are similar to those obtained for the case study 1 (see Figures 5.9 to 5.12). However, a much shorter time is needed in this case by L and V to achieve steady stated. For case study 1, L

and V increments to obtain the setpoints were about 0.37 kmol/min. For case study 2, these increments are around 0.005 kmol/min.

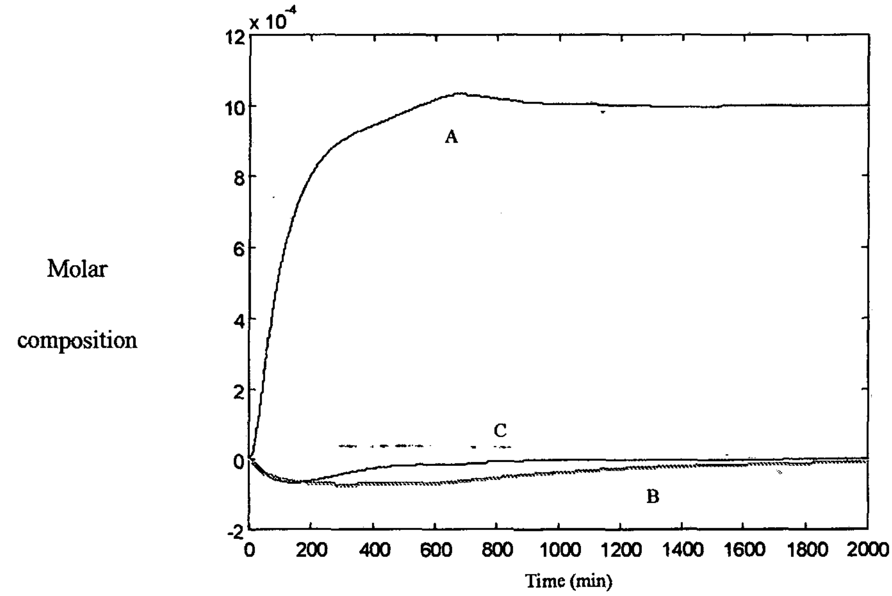

Figure 5.37: Output profiles for a setpoint change in A composition

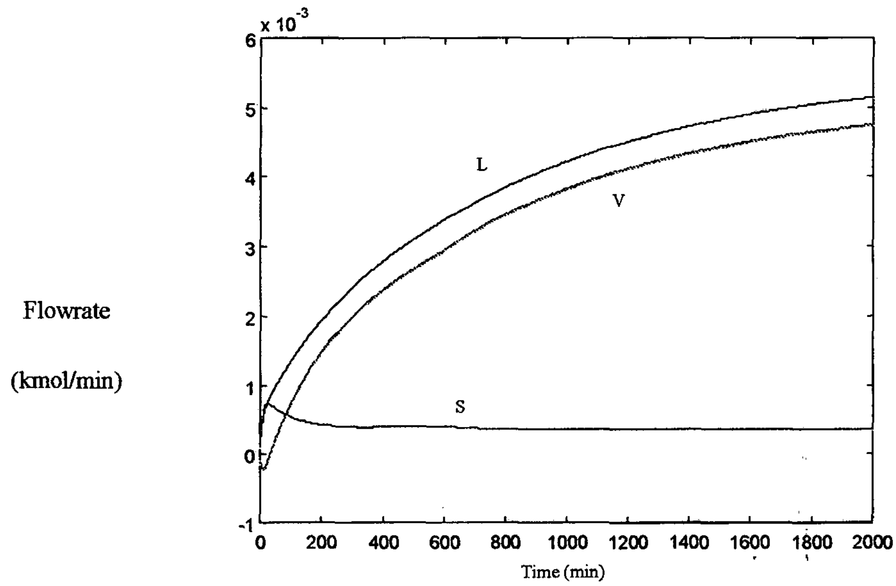

Figure 5.38: Input profiles for a setpoint change in A composition

With the same tuning (Δt=1, n=600, p=300, m=6, $k2$=100) but $k2$=10, settling times are shorter, but deviations are larger and profiles a little irregular. With Δt=1, n=600, p=30, m=8, $k2$=100, an oscillating response is obtained. With the aim of having a small p covering a larger time, the tuning Δt=3, n=200, p=30, m=8, $k2$=100 has been considered. However, simulation results indicate a bad performance. A tuning giving a quicker response and good performance is not found.

Diagonal feedback behaviour for the same setpoint change has been simulated. Tuning is K_c=0.29, τ_c=78 (loop L-x_{AD}), K_c=-1.21, τ_c=80 (loop S-x_{BS}), K_c=0.24, τ_c=80 (loop V-x_{CB}). With this tuning, max(σ(wi*Ti)) is smaller than 0.4. Simulation results are shown in Figures 5.39 and 5.40. As was found for case study 1, with the PI controllers, faster responses are obtained, but also larger deviations in B and C compositions. Comparing case studies 1 and 2, the difference between closed-loop time constants for both control strategies has shortened.

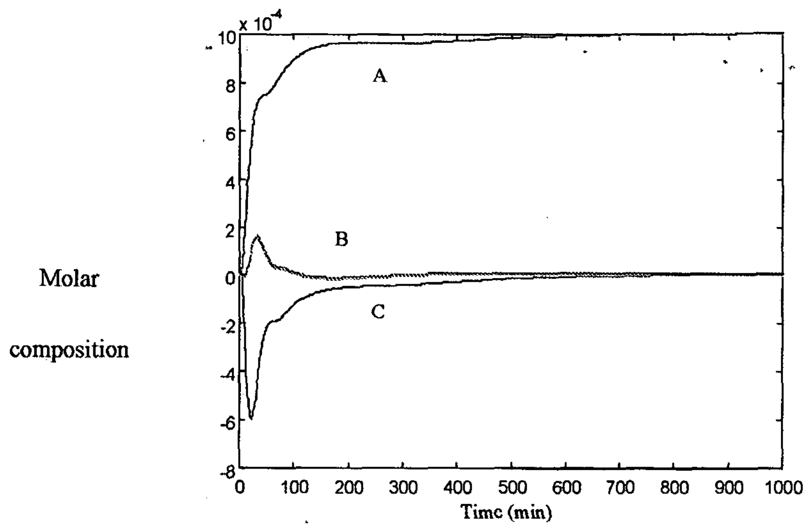

Figure 5.39: PI output profiles for a setpoint change in A composition

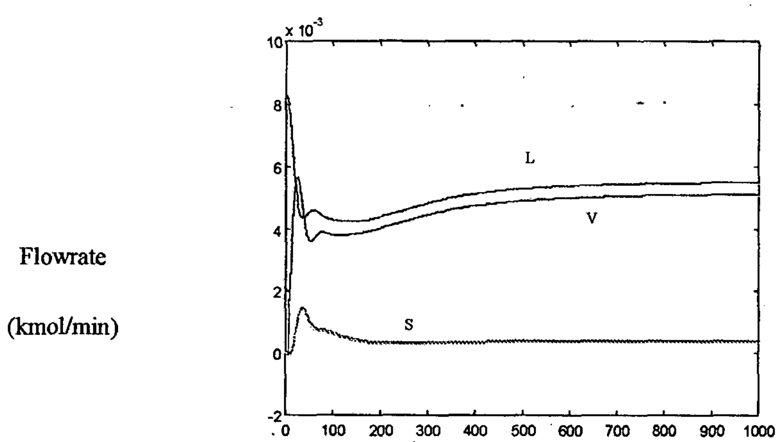

Figure 5.40: PI input profiles for a setpoint change in A composition

For the rejection of a disturbance of +0.1 kmol/min in F, the DMC behaviour has been simulated. Tuning is Δt=1, n=600, p=300, m=6, λ(1,1)=14, λ(2,2)=14, λ(3,3)=60. Results are shown in Figures 5.41 and 5.42, where it is seen that a large overshoot in C composition is obtained.

Molar

composition

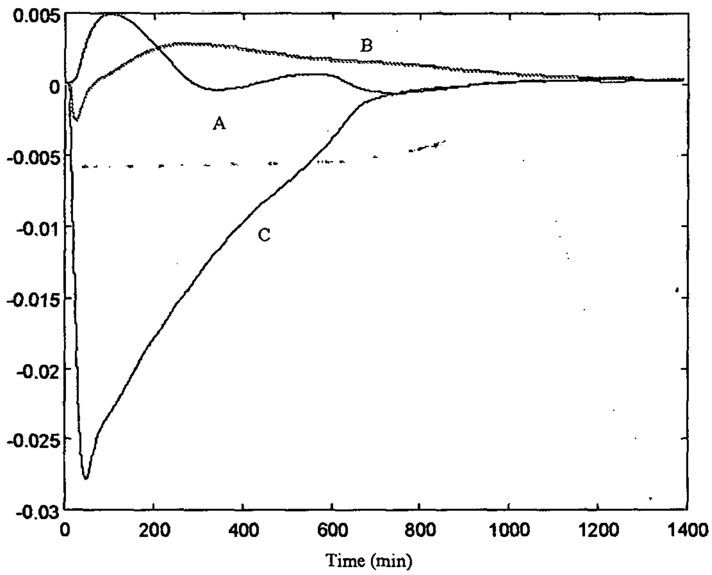

Figure 5.41: Output profiles for a disturbance in F

Flowrate

(kmol/min)

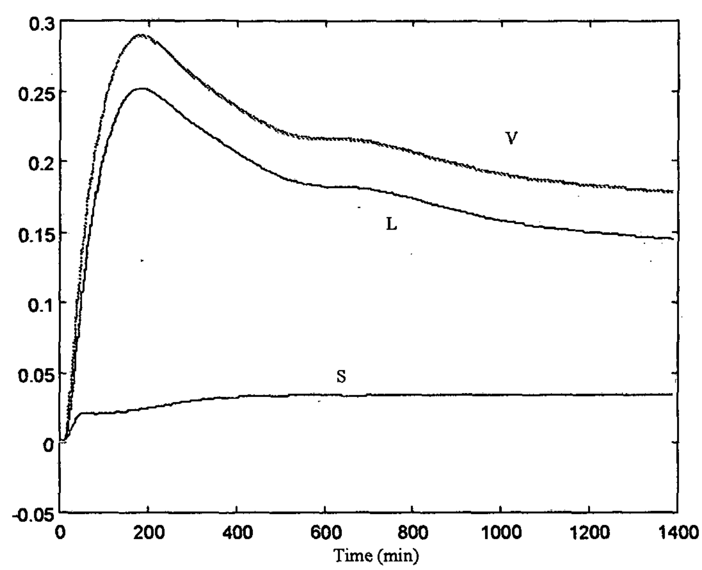

Figure 5.42: Input profiles for a disturbance in F

Feedback control behaviour for the rejection of the same disturbance has also been simulated. Results can be seen in Figures 5.43 and 5.44. Tuning is K_c=0.29, τ_c=78 (loop L-x_{AD}), K_c=-1.21, τ_c=80 (loop S-x_{BS}), K_c=0.24, τ_c=80 (loop V-x_{CB}). Overshoots are two times smaller than with DMC. On the other hand, steady state is achieved in a shorter time.

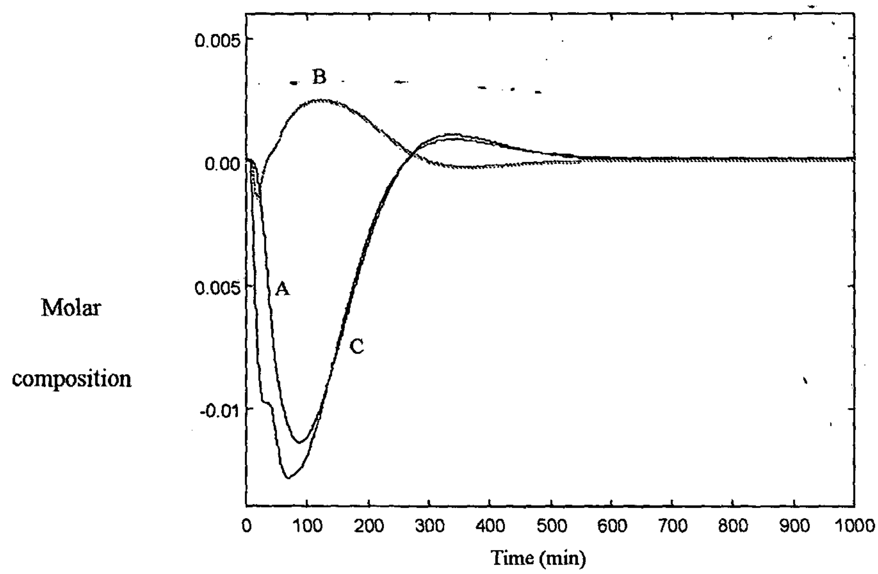

Figure 5.43: PI output profiles for a disturbance in F

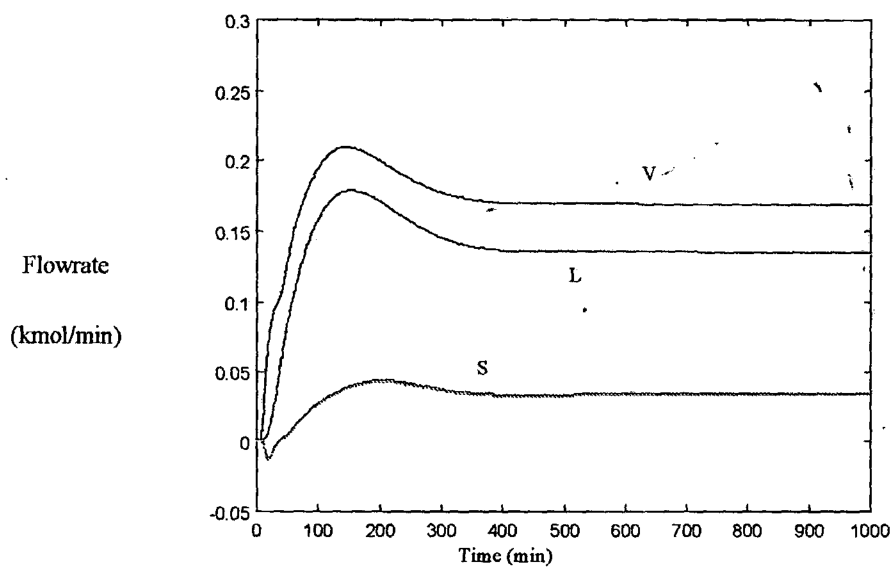

Figure 5.44: PI input profiles for a disturbance in F

Therefore, results are similar for both case studies: DMC setpoint tracking has smaller deviations but longer closed-loop time constants, and worse performance for disturbance rejection. For this case study however, differences between DMC and feedback control strategies seem smaller. This would indicate that DMC is favoured by long DWC.

In Figures 5.45, 5.46, and 5.47, ***RDG*** for case study 2 are plotted. Comparing Figures 5.34 to 5.36 with Figures 5.45 to 5.47, a general trend is not found. Values have increased for some ***RDG*** elements and decreased for others. The different ***RDG*** elements behaviour make difficult to conclude if interactions favour disturbance rejection more in one case than in the other.

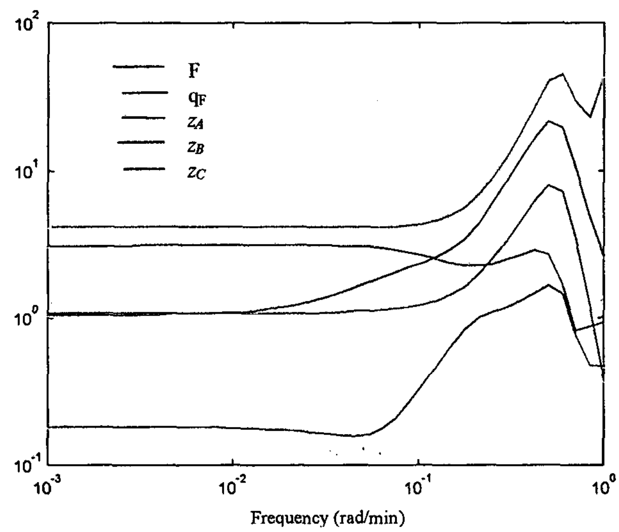

Figure 5.45: ***RDG*** elements for output 1

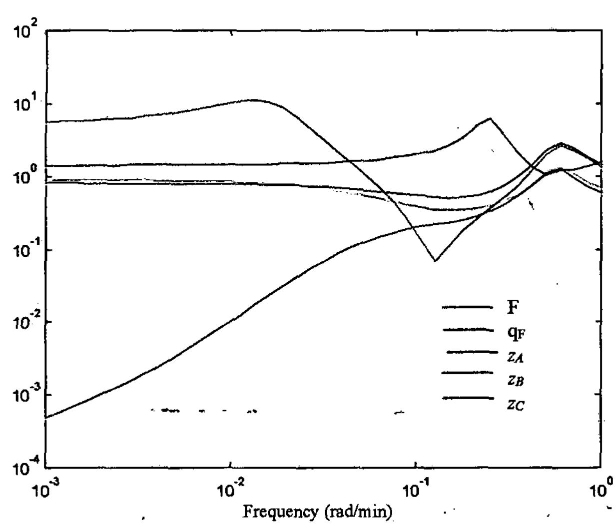

Figure 5.46: ***RDG*** elements for output 2

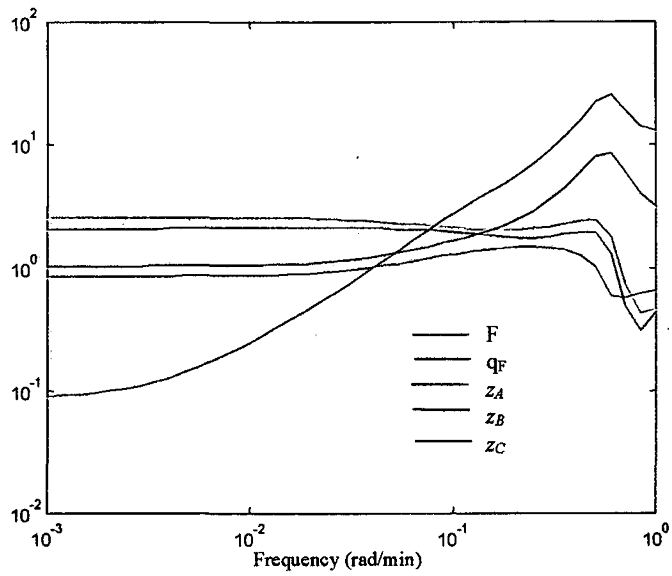

Figure 5.47: ***RDG*** elements for output 3

5.10 DMC for a DWC with "DB" inventory control and composition control *L SPLITD S*

In chapter four, it was seen that the best composition control structure for the separation problem described in 4.3.1.2 and "DB" inventory control was *L SPLITD S*. For that example, operation was not optimal. For the same separation example at the same operating conditions and the same control structure, DMC behaviour is simulated for a setpoint change of +0.001 in A purity. Tuning is Δt=1, n=600, p=300, m=6, $k2$=100. Resulting profiles can be seen in Figures 5.48 and 5.49, where it can be seen that deviations in output variables are very small and the time needed to achieve steady state is acceptable.

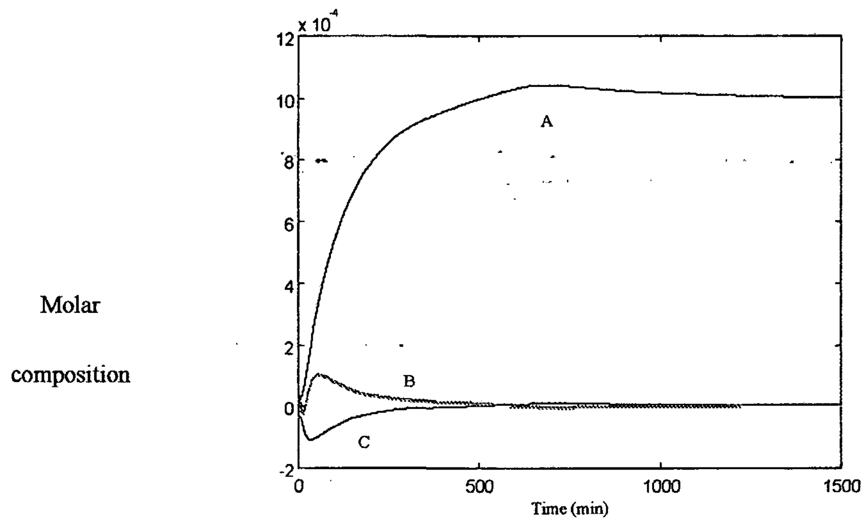

Figure 5.48: Output profiles for a setpoint change in A purity

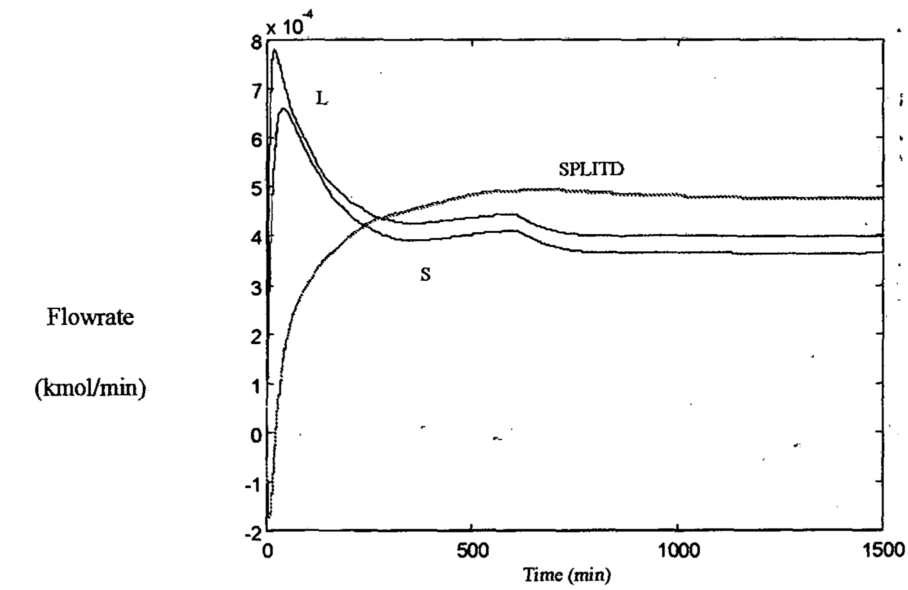

Figure 5.49: Input profiles for a setpoint change in A purity

To compare the performances of DMC and diagonal feedback control, the behaviour of PI controllers for the same setpoint change has also been simulated. Results are shown in Figures 5.50 and 5.51. Tuning was K_c=0.073, τ_c=73 (loop L-x_{AD}), K_c=0.089, τ_c=17.8 (loop S-x_{BS}), K_c=0.59, τ_c=65.5 (loop V-x_{CB}). Deviations in B and C compositions are large compared to the ones found with DMC. However, profiles are more regular and stability is got quicker.

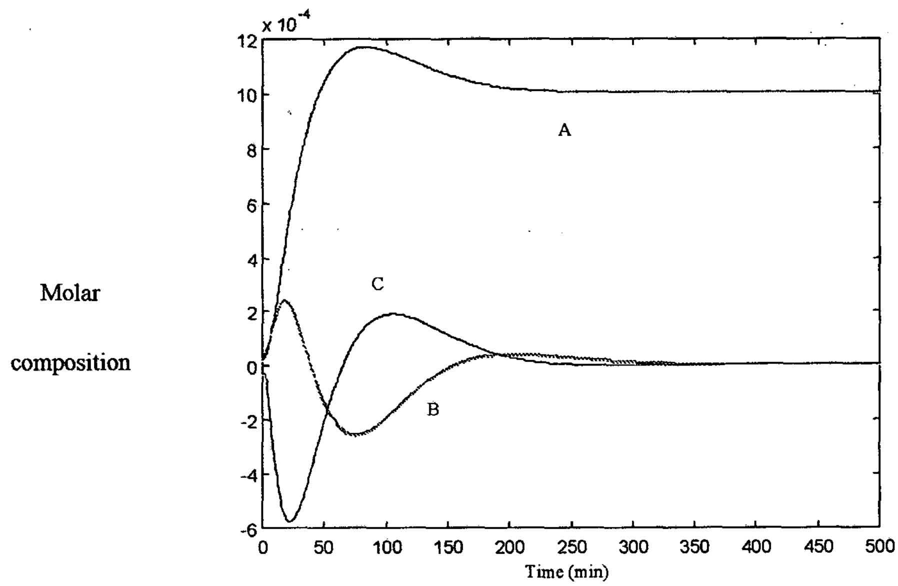

Figure 5.50: PI output profiles for a setpoint change in A purity

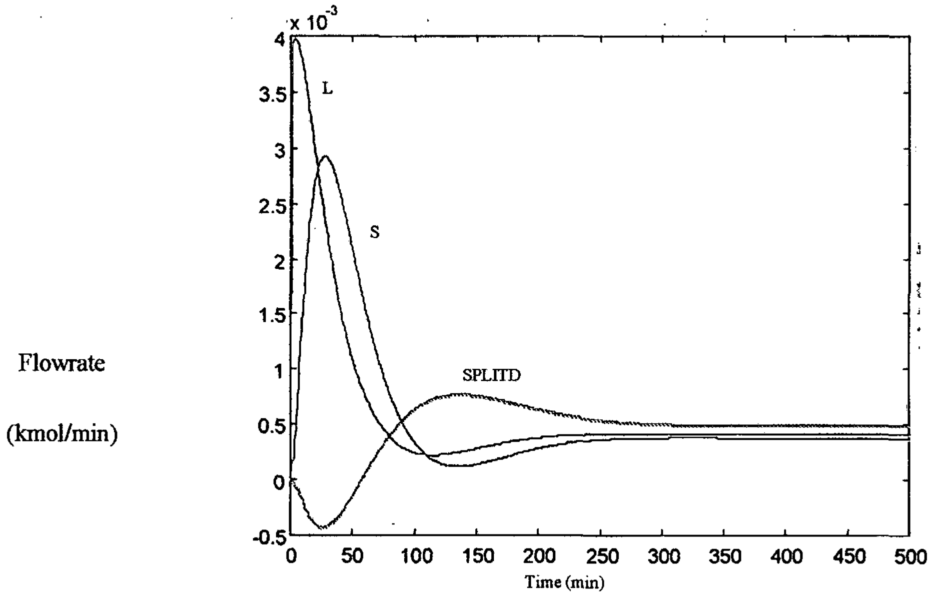

Figure 5.51: PI input profiles for a setpoint change in A purity

It is important that DMC has the flexibility to be used with *L SPLITD S* structure, which is the preferred one in terms of controllability, for some operating conditions. The reduction of the directionality problem with *L SPLITD S* structure seems to favour DMC performance.

5.11 Non-linear Model Predictive Control

The heart of MPC is the process model itself. It has a large impact on the MPC ability to control. For mildly non-linear processes, and for close regulatory control of arbitrary non-linear processes near steady state, it is entirely reasonable to use a linear model. However, when non-linearity is strong, and for sufficiently large excursions from the steady state, more effective alternatives must be considered.

From the simulations in this chapter, it can be concluded that in general, diagonal feedback control performs better than DMC for the control of the DWC. Therefore, it would be very interesting to consider non-linear MPC.

There is no fundamental impediment for the use of a non-linear DWC model in MPC. However, some serious practical issues arise that make the use of a non-linear model a nontrivial exercise. The procedure for carrying out the model inversion required for the implementation of the standard MPC controller is itself not trivial.

5.12 Conclusions

Process identification is required to build the DMC model. The sign and the size of the steps used for the process identification have been found to have a very large influence over the DWC model and over the DMC performance. This is because of the DWC non-linearity. The preferred models are found with very small identification steps.

For "LV" stabilised DWC, DMC is not appropriate. The reason is the instability of the open-loop system. In this sense, feedback control strategy is superior to DMC because it can be applied to a system with singular steady state gain matrix.

According to simulations, for moderate purity distillations, both DMC and diagonal feedback control may perform the DWC composition control with "DB" *L S V* structure. However, DMC performance is unacceptable in some cases. In order to compare the two control strategies, two different columns have been studied. One of them has more trays and better controllability. In both cases, a similar behaviour has been found. Diagonal feedback control has a better control over the closed-loop time constants. DMC tuning parameters have a weak influence on the control performance. For setpoint changes, DMC presents smaller deviations. For disturbance rejection, overshoots are smaller with diagonal feedback control. In general, differences between DMC and diagonal feedback control are shorter for the column with more trays, for which the controllability indexes are better.

DMC has a great difficulty to control the DWC when *L* and *V* manipulated variables increase with similar ratio in order to move A and C compositions in the same direction. In this situation, due to a high directionality, gains are much smaller than the gains found by identification. PI controllers also have difficulty to control the DWC in this situation. However, they are more able to overcome it.

DMC, as well as diagonal feedback control, may be implemented with "DB" *L SPLITD S* control structure. This structure is the preferred one for some DWC non-optimal operations. The directionality of this control structure is weaker than the directionality of "DB" *L S V*, and DMC inferiority seems smaller. This result also indicates that DMC accuses directionality problems more than the diagonal feedback control.