CHAPTER V

CONTROL SYSTEM APPLICATION

The control system used the MPC technique to track the composition of cyclohexane at the condenser of BD column with optimal reflux ratio policy is presented in this chapter. For the general MPC, the accuracy of the process model is very significant. If the model predicts future values of the outputs incorrectly, the performance of control can be worst, instead of better. As mentioned in the previous chapter, the NN approach can be identified the behavior of the process exactly. Therefore, the model based on the NN approach is employed to predict the future output in this controller.

The simulation of this control system is divided into two sections as follows: *off–line* and *on–line* calculation systems, which is illustrated using the block diagram as shown in Figure 5.1. The first section is presented the calculation in off-line system which has the goal to determine the profile of cyclohexane composition at the condenser which is employed as the setpoint profile ($x_{D1,SETPOINT}$) of the controller in on-line system. This section consists of two steps: optimal control and system simulation. In optimal control step, the optimal reflux ratio profile ($r_{OPTIMAL}$) can be determined from solving the optimization problem defined in term of the maximum distillate product. Then, that profile will be used in the mathematical model for simulating the process behavior involved the setpoint profile.

Next section shows the control system employed the MPC technique based on NN model as the NNMPC controller to determine the manipulated variable (r). For the NN model, the same procedure to determine the appropriate network described in chapter IV is employed under the different network structure which its details will be explained in the following. The manipulated variable employed in the actual process, mathematical model, is the first value of r profile determined from solving the optimization problem that has the objective to track $x_{D1,SETPOINT}$.

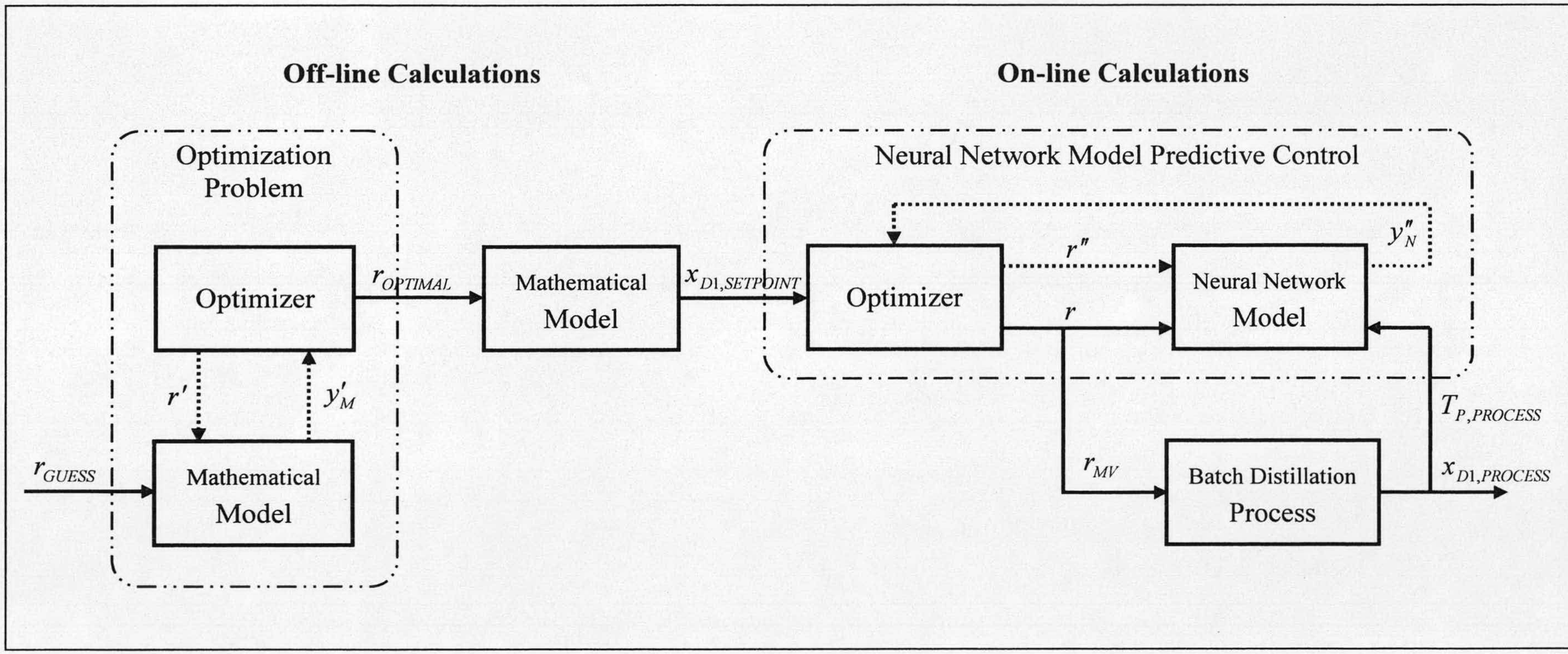


Figure 5.1 Control system block diagram

Moreover, the performance and robustness of the controller is also presented in the following. The robustness of the controller is tested under NN model and process parameter mismatches.

5.1 Off–line System

As mentioned before, the setpoint profile used in the controller can be determined from the calculation in off-line system which is divided into two steps: *the optimal control* and *process simuiation*. The optimal control is studied for solving $r_{OPTIMAL}$ which will be employed to simulating the process behavior for solving $x_{D1,SETPOINT}$.

5.1.1 Dynamic Optimization

In this work, the dynamic optimization can be defined in term of maximum of the distillate product collected at the accumulator to determine $r_{OPTIMAL}$ subject to the constraints on the BD system as follows: the mathematical model, the batch time, the purity of the product at the end of process, and the boundary of the reflux ratio, which can be written as:

$$\underset{r(t)}{Max} \quad H_A \tag{5.1}$$

s.t.	Model equations	(equality constraints)
	$t = t_F$	(equality constraints)
	$x_{A1} \geq x_{A1}^*$	(inequality constraints)
	$r_L \leq r \leq r_U$	(inequality constraints)

where H_A is the amount of product at the condenser, r is the reflux ratio profile to be optimized, x_{A1} is the purity of accumulated product, x_{A1}^* is the specified purity of accumulated product, t is a time of operation, t_F is a fixed time of operation, and r_L and r_U are lower and upper bounds of the reflux ratio. The optimization problem is solved by using sequential quadratic programming (SQP) method.

In the simulation of optimization, the system can be simulated under the condition as follows: t_F is fixed at 2.62 hours, r is bounded between 2/3 of r_L and 20/21 of r_U, and x^*_{A1} is no less than 89.5 percent. For optimal control study, the profiles of $r_{OPTIMAL}$ is concerned with a piecewise constant. The interval of each profile can be determined by dividing the fixed operation time with the number of interval varied from one to eight intervals.

- ***Simulation Result***

The simulation results of all case studies show in the following figures which figure (a) shows the profile of the optimal reflux ratio. Figure (b) shows the composition profile of the product at the accumulator which the solid line represents the profile of cyclohexane, the dash line represents the profile of n-heptane, and the dot line represents the profile of toluene.

<u>*One time interval*</u>

In this case, the reflux with constant value along the batch time is studied which its results are shown in Figure 5.1. The optimal reflux ratio obtained from solving the optimization problem is equal 0.83807 and the amount of product is 1.1666 kmol.

<u>*Two time intervals*</u>

The time interval of the reflux profile is increased to be equal two intervals. The optimal reflux ratio of the first and the second intervals are 0.77542 and 0.88951 respectively which provide the amount of product to 1.2071 kmol. The simulation result under this optimal profile shows in Figure 5.2.

<u>*Four time intervals*</u>

The simulation results obtained by using the optimal reflux ratio with four time intervals are shown in Figure 5.3. The values of the optimal reflux ratio at each interval are 0.72129, 0.8278, 0.88859, and 0.88873 respectively. The amount of product increases to 1.2133 kmol.

Eight time interval

Figure 5.4 shows the result of the optimal reflux ratio profile with eight intervals which each interval has the value of the optimal reflux ratio to be 0.69, 0.76785, 0.8089, 0.84054, 0.87024, 0.88932, 0.93498, and 0.84371. The product quantity is 1.2199 kmol.

- ***Results and Discussion***

In this section, the optimal control is studied in order to obtain the optimal reflux ratio profile employed to generate the setpoint profile. The results of all case studies are summarized in Table 5.1. It can be seen that the optimal reflux ratio profile with only one interval provides the amount of product to be equal 1.1666 kmol, whereas that profile with eight intervals provide the product increase to 1.2199 kmol. This means that the improvement of the product quantity can be done by increasing the number of time intervals of the optimal reflux ratio profile. In addition, the effect of the interval number increase on the product composition is analyzed. That profile is smoother close to a constant value of the specify purity along the batch time. However, the selection of the appropriate number of interval should be concerned due to the amount of product is improved with a small value and the optimization time is large when a lot of intervals are used.

Table 5.1 The amount of product and that composition using optimal reflux policies with different time intervals.

The Number of Interval	The Amount of Product (kmol)	Percentage of Increasing the Amount of Product
1	1.1666	Base case
2	1.2071	3.4716
4	1.2133	4.0031
8	1.2199	4.5688

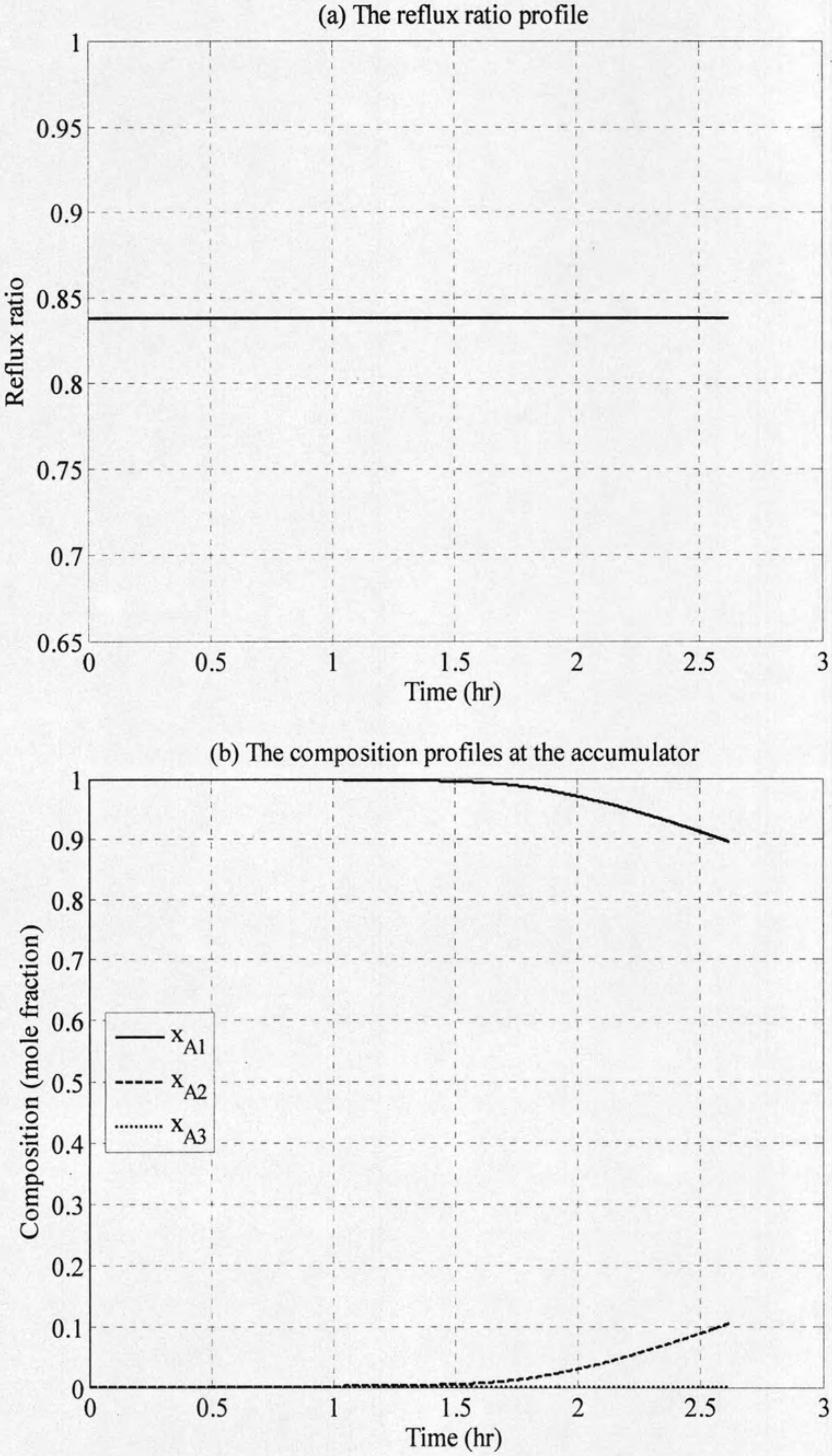


Figure 5.2 Process response from using a constant optimal reflux profile

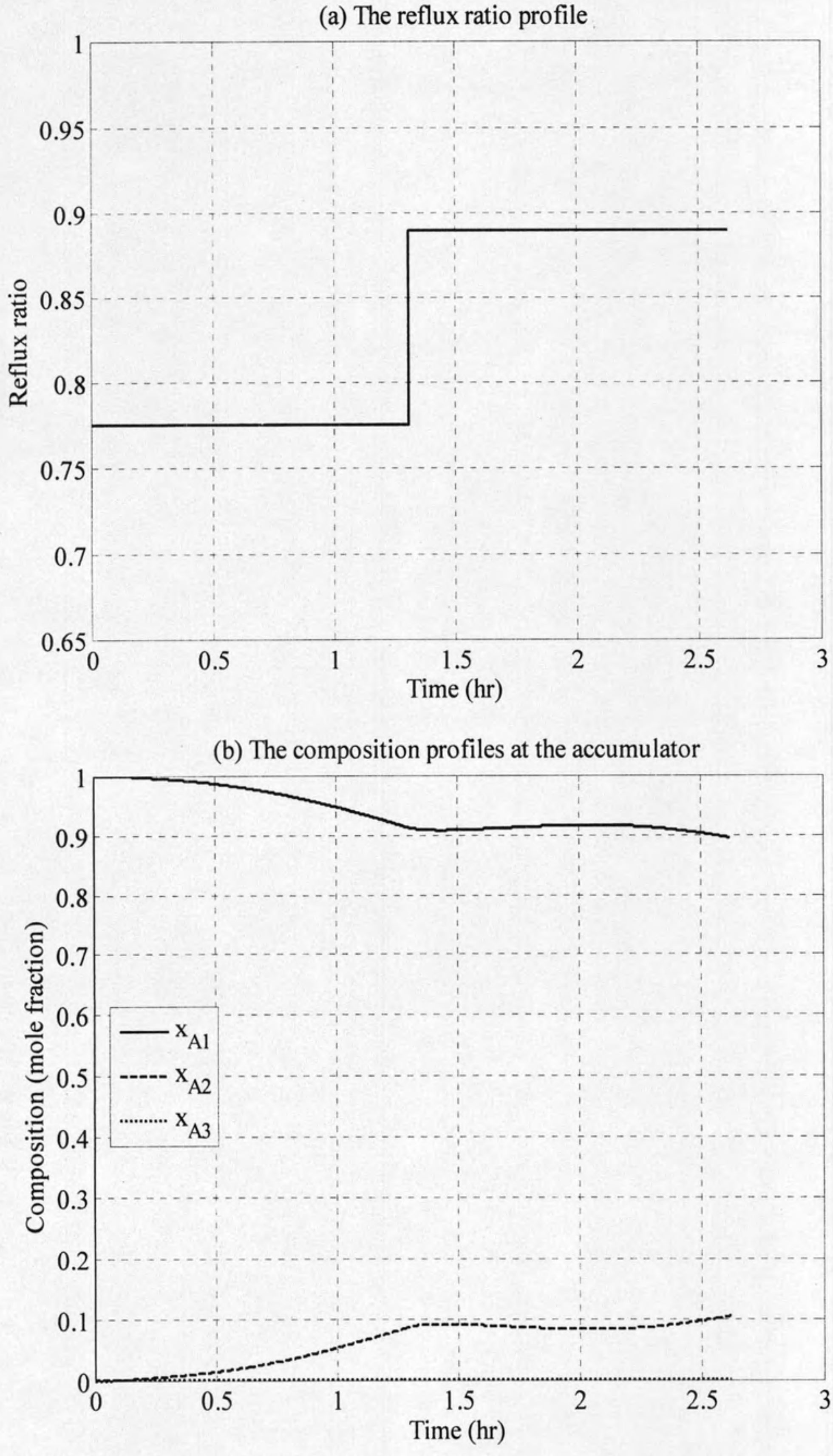


Figure 5.3 Process response from using two constant optimal reflux profile

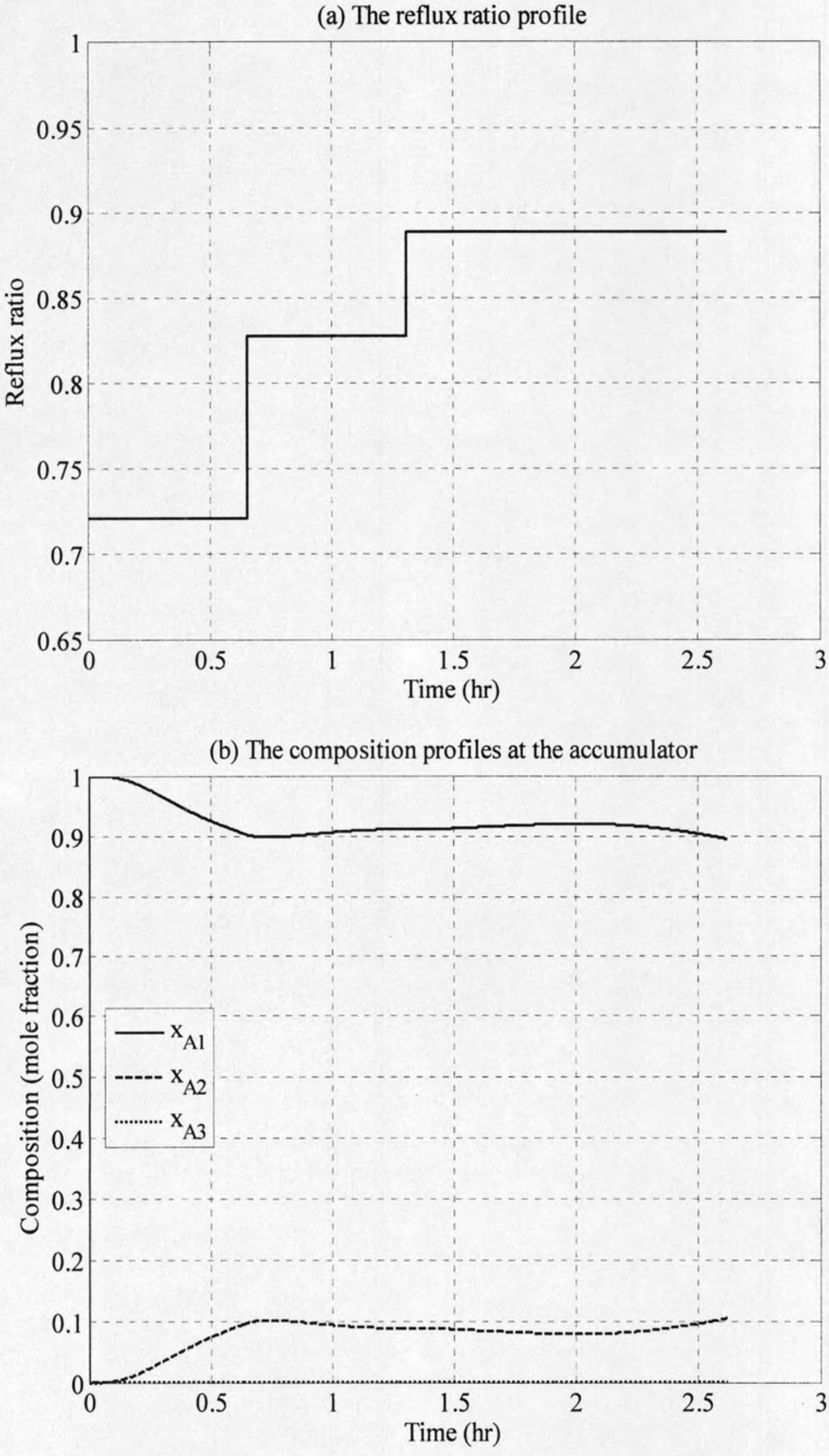


Figure 5.4 Process response from using four constant optimal reflux profile

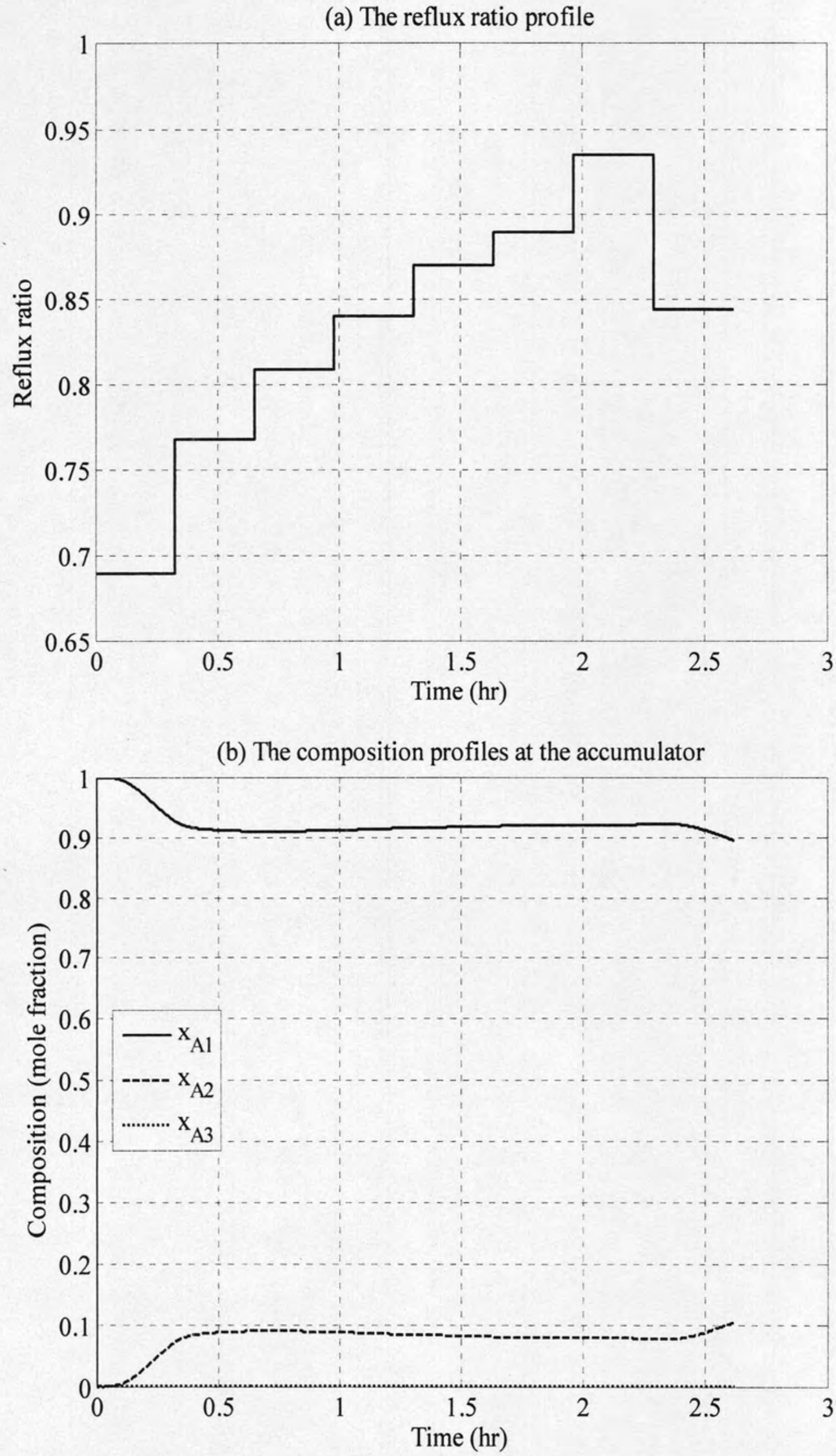


Figure 5.5 Process response from using eight constant optimal reflux profile

Note that the value of the optimal reflux ratio at each interval increases along the batch time except at the final interval which that value significantly decrease. Due to the purity of product is an unsatisfying value, the reflux flow will be decreased for adjusting the product purity to satisfy the specify purity.

5.1.2 Process Simulation

The aim of this section is to generate the profile of $x_{D1,SETPOINT}$ using the profile of $r_{OPTIMAL}$ determined from 5.1.1 section. The profile of $r_{OPTIMAL}$ with eight intervals is selected due to the limitation of the optimization time. The mathematical model mentioned in chapter IV is employed to simulate the BD process under this condition, which the simulation result of the cyclohexane composition at the condenser is shown in Figure 5.5.

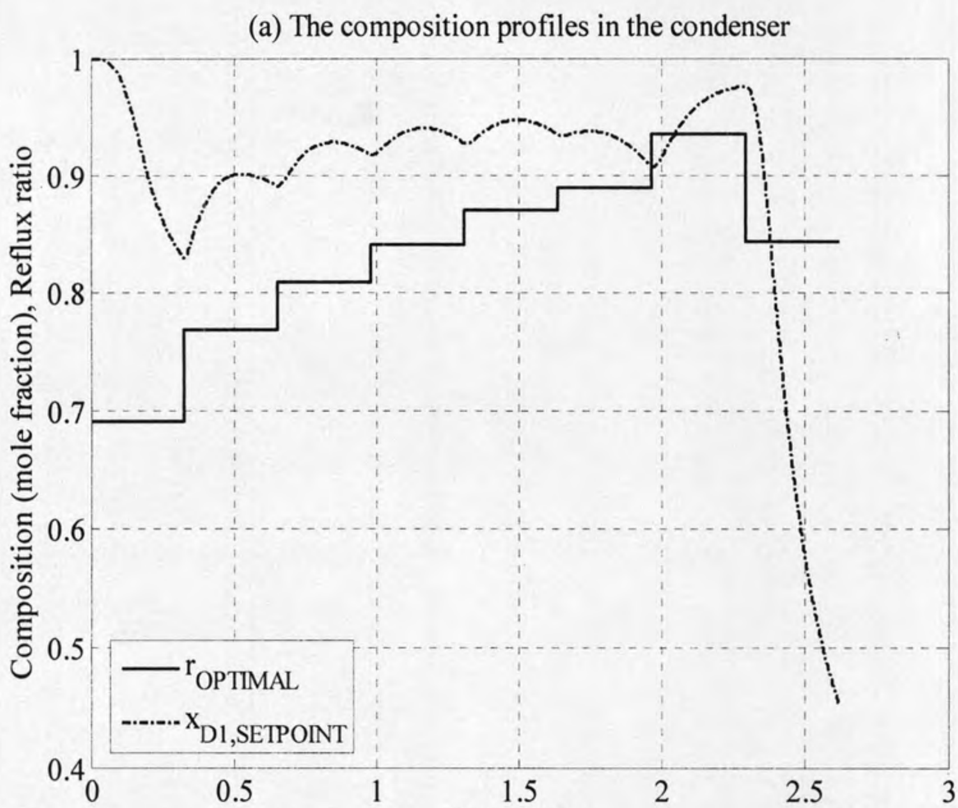


Figure 5.6 Response of cyclohexane composition at the condenser used the optimal reflux profile with eight constant

5.2 On–line System

In this section, the MPC technique based on NN model called *neural network model predictive control* (NNMPC) is employed in the control system of BD process to track the $x_{D1,SETPOINT}$ profile. The controller consists of the process model determined by using NN approach and optimization problem solved by using SQP which both details will be present in the section of NNMPC controller. Moreover, the performance and robustness test of the controller is also presented in the final section.

5.2.1 NNMPC Controller

The NNMPC controller is formulated using the MPC control technique base on the NN model. The NN model predicts future output over the prediction horizon. The predictions are provided to the optimizer to determine the values of the control action over the control horizon which the control system diagram is shown in Figure 5.11. The details of NN modeling and the formulation of the optimization problem used in the NNMPC controller are shown in the following. Moreover, the integrated absolute error (IAE) is also presented to evaluate the control performance.

- ***NN Modeling***

Generally, the relationship between controlled variable and manipulated variable are included in the model used in the model based controller. In this work, the NN approach mentioned in chapter IV is employed for modeling the behavior of BD process used in the controller. For the determination of NN model, the basic process variables especially the controlled variable and the manipulated variable should be included in the model input. However, the input data based on the measured variables is concerned for determining the appropriate network. Due to the cyclohexane composition at the condenser which is the controlled variable can not be measured with on-line system. Therefore, the secondary process variable as well as temperature is considered as the model input instead of the composition.

As mentioned in chapter IV, it can be seen that the input variables which consists of the temperature measured with five locations and reflux ratio is used as the input data. To improve the accuracy of NN model, the data input should consist of the current and past values of the input variables. Therefore, the data used for determining the appropriate network is shown in Figure 5.7.

For the determination of the appropriate network employed for predicting the future composition, the network design and the determination algorithm are the same as the descriptions in chapter IV. The appropriate configuration of NN model can be determined by varying the number of hidden nodes from two to ten nodes per each hidden layer which the result is shown in Table 5.2. Note that, the NN with two hidden layer is considered.

The results for determining the appropriate network are concluded in Table 5.2. It can be seen that the appropriate configuration of NN model that consists of an input with twelve nodes, an output with seven nodes, and two hidden layers with ten nodes for each layer ($12-10-10-7$) shown in Figure 5.7. The performances of the network modeling are 2.05×10^{-4} of train error, 3.77×10^{-4} of validation error, and 3.81×10^{-4} of test error.

In addition, the appropriate network is also to test the network capability using the simulation under base case condition which results are shown in Figure 5.8 and Figure 5.9, and the percentage of RAE are shown in Table5.3. It can be seen that the prediction is quite good especially for the prediction of the temperature due to the input data depend directly on the future temperature.

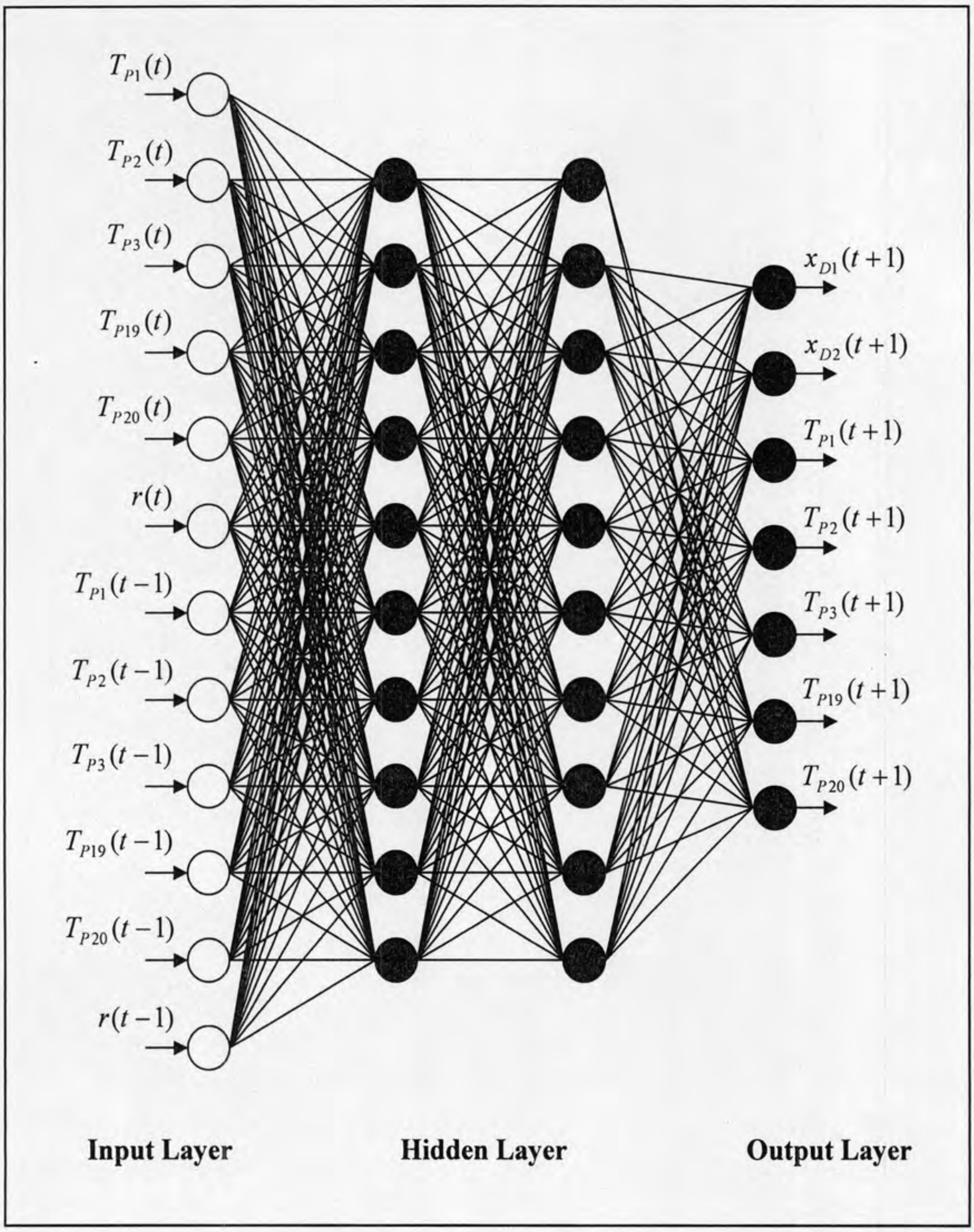


Figure 5.7 Multilayer NN with two hidden layers representing the model in NNMPC controller.

Table 5.2 Effect of the number of hidden nodes in two hidden layer representing the model in NNMPC controller on the MSE obtained with the training, validation, and test sets.

Number of nodes		Training error	Validation error	Test error
S1	S2	$\times 10^{-3}$	$\times 10^{-3}$	$\times 10^{-3}$
2	2	8.6709	9.1623	10.336
	4	5.0125	5.8297	6.1275
	6	1.6042	1.9526	2.5943
	8	1.2916	1.8315	2.4912
	10	1.3663	1.7583	2.3657
4	2	86.584	13.637	14.403
	4	0.63199	0.80908	0.94384
	6	0.28526	0.62980	0.76827
	8	0.25794	0.64952	0.81138
	10	0.27743	0.61669	0.71961
6	2	8.6392	9.3524	10.290
	4	0.60396	0.73495	0.87794
	6	0.21498	0.38369	0.38742
	8	0.23725	0.54922	0.59013
	10	0.23725	0.54922	0.59013

Table 5.2 Effect of number of nodes in two hidden layer representing the model in NNMPC controller on the MSE obtained with the training, validation, and test sets (continued).

Number of nodes		Training error	Validation error	Test error
S1	S2	$\times 10^{-5}$	$\times 10^{-5}$	$\times 10^{-5}$
8	2	11.208	26.029	44.102
	4	0.58044	0.65051	0.77796
	6	0.22838	0.51645	0.56908
	8	0.21095	0.40738	0.42732
	10	0.2086	0.4372	0.48824
10	2	8.6222	9.1760	10.280
	4	0.57958	0.68738	0.77148
	6	0.21649	0.52663	0.54361
	8	0.21010	0.41866	0.46861
	10	**0.20452**	**0.3765**	**0.38063**

Table 5.3 The percentage of RAE of the simulation results of NN model in NNMPC controller ($12-10-10-7$) compared with the base case results

Output	% RAE
Top composition of Cyclohexane (x_{D1})	0.18994
Top composition of n–Heptane (x_{D2})	19.232
Temperature at the condenser (T_{P1})	0.0051893
Temperature of plate No. 2 (T_{P2})	0.017451
Temperature at the plate No. 3 (T_{P3})	0.027876
Temperature at the plate No. 19 (T_{P19})	0.0046786
Temperature at the reboiler (T_{P20})	0.0036765

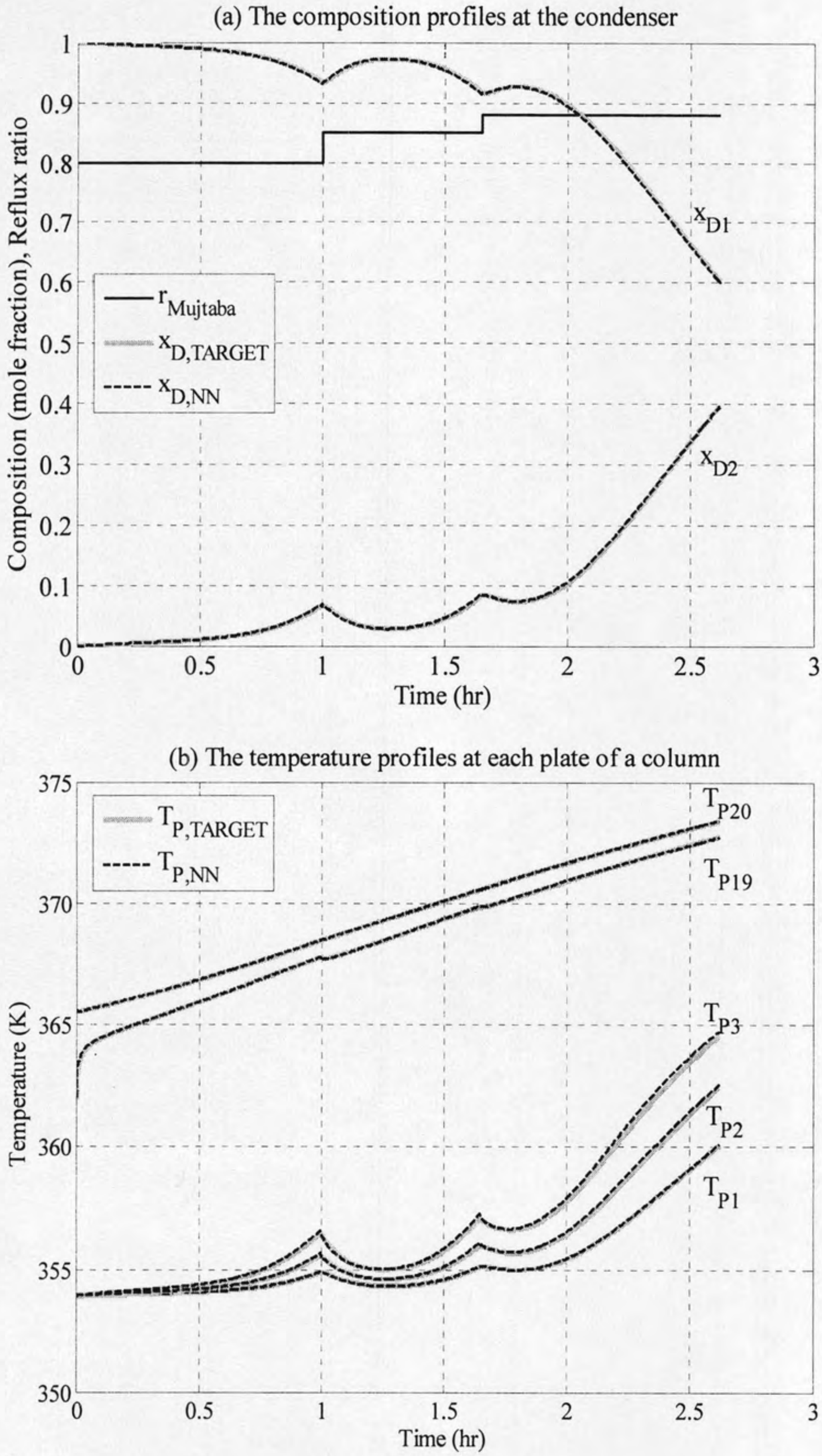


Figure 5.8 Comparison of output profiles calculated from the mathematical model and the NN model in NNMPC controller $(12-10-10-7)$

- ***Optimization Problem in NNMPC***

Typically, the objective functions of the MPC controller include two terms: *variance between the process output and the setpoint*, and *a penalty on the control variance* as shown in the following.

$$\underset{r(t)}{Min} \quad \sum_{t=0}^{N_{PREDICT}} W_1(x_{D1} - x_{D1,SETPOINT})^2 + \sum_{t=0}^{N_{CONTROL}} W_2(\Delta r)^2 \tag{5.2}$$

s.t. NN model (equality constraints)

$r_L \leq r \leq r_U$ (inequality constraints)

where x_{D1} is the purity of distillate product, $x_{D1,SETPOINT}$ is the setpoint purity of distillate product, r is the reflux ratio profile to be optimized, $N_{PREDICT}$ is the prediction horizon, $N_{CONTROL}$ is the control horizon, W_1 and W_2 are weighting factors, and r_L and r_U are lower and upper bounds of the reflux ratio.

- ***Performance Evaluation***

The index evaluates the control performance using integrated absolute error (IAE) as shown in the following.

$$IAE = \int_0^{t_F} |e(t)| dt \tag{5.3}$$

where $e(t)$ is the error deviated from the setpoint at time t, and t_F is the batch time of operation.

5.2.2 BD Control Using NNMPC controller

This section presents the application of the NNMPC controller to control BD process. The control objective is to track the cyclohexane composition at the condenser with an optimal reflux ratio profile obtained from the previous section and to evaluate the control performance. To test the performance of NNMPC controller based on the accuracy NN model (the network with two hidden layer), the optimal reflux ratio profile with eight time intervals mentioned in the previous section is employed as the setpoint in the nominal case. Moreover, the robustness of the controller is evaluated under two conditions of the model-plant mismatch: *model-plant mismatch caused by NN model* and *model-plant mismatch caused by process change*. The NN with only one hidden layer is selected as the mismatch of NN model. The mismatch of process change comes from the varying of the rate of vapor flowed from the top column to the condenser, and the liquid holdup at the condenser.

- ***Nominal Case***

In the nominal case, the controller is tuned with the prediction horizon ($N_{PREDICT}$) as two, the control horizon ($N_{CONTROL}$) as one, and weighting factor (W_1 and W_2) as one. The performance of the controller under this case evaluated using IAE is 259.2389. The amount of distillate product is 1.1933 kmol and that composition is 0.90955. The results are show in Figure 5.9, it can be seen that the tracking of cyclohexane composition profile is a sluggish response. At the first and final periods of the operation time, the control action is more overshooting and oscillating responses. These actions may be occurred when the tuning parameter is not appropriate.

- ***Model-plant mismatch caused by NN model***

In the case of NN model mismatch, the results are shown in Figure 5.10. The response of tracking cyclohexane composition profile is faster control action than the nominal case. The tracking capability presents more off-sets along batch time. However, the NNMPC shows robust tracking capability at the last period of batch. This robustness may be comes from an inherent fault-tolerant character due to the massive parallelism in the NN. The values of IAE is 310.5389, the amount of product is 1.2365 kmol, and the product composition 0.8848 as shown in Table 5.28.

- ***Model-plant mismatch caused by process change***

The control performance when the process changes are tested under the conditions as the following:

The vapor flow at the top column (V_1) change: + 30% of V_1

The control responses under the condition of increasing the vapor flow at the top column are shown in Figure 5.11. The NNMPC controller shows quite good control performance, the value of IAE is 255.3162. However, the manipulated variable still oscillates response. The product is obtained as 1.2673 kmol and its composition is 0.91331.

The vapor flow at the top column (V_1) change: – 30% of V_1

From Figure 5.12, it can be seen that the response of tracking cyclohexane composition profile is very sluggish. Moreover, the manipulated variables present drastic variation at the final period of batch time. This led to the unsatisfied product which has 1.0430 kmol of its quantity and 89.935% of its purity. The performance of controller under this case is 267.8650 of IAE.

The liquid holdup at the condenser (H_C) change: + 30% of H_C

The responses of NNMPC under the liquid holdup of the condenser increasing to 30% are shown in Figure 5.13. The control action is the same as that in the nominal case, except the last period time which the manipulated variable present oscillate action. The performance of the controller in this case is 293.0011. The product quantities is 1.2558 kmol and its composition is 0.88205

The liquid holdup at the condenser (H_C) change: – 30% of H_C

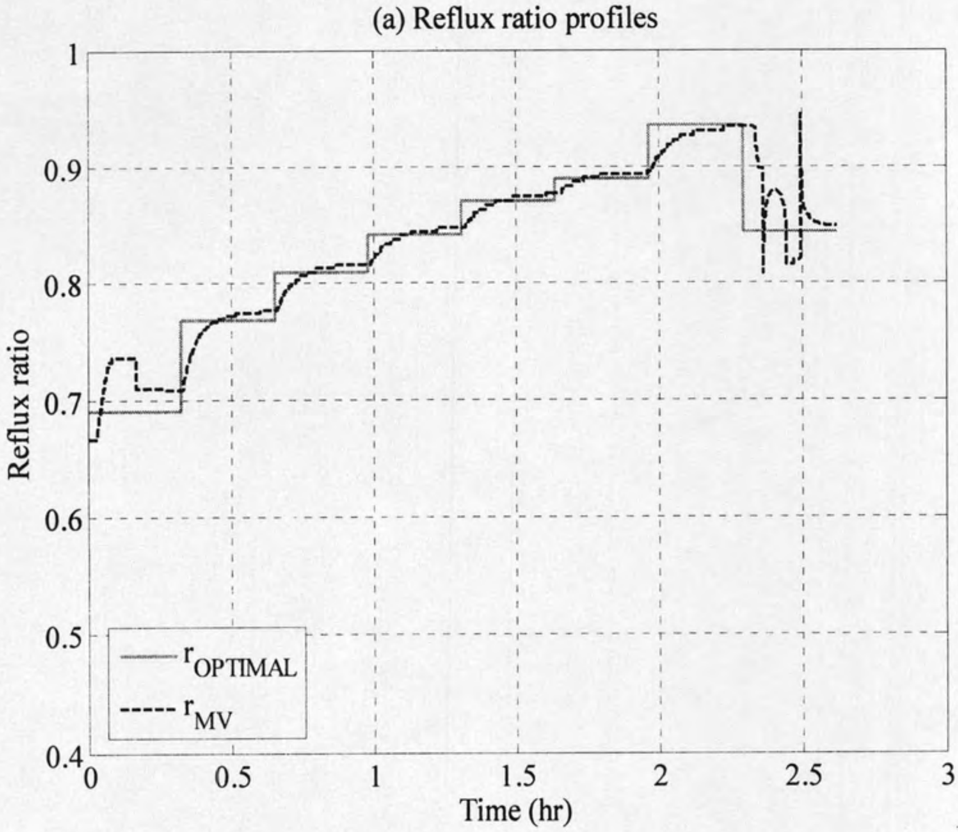
Figure 5.14 are shown the response of cyclohexane composition at the condenser and the accumulator. The performances of this controller are 231.0231 of IAE Observe that, the response is the same as that in the nominal case and the case of H_C increasing (see the result in the previous result), except the response in the final period of batch time which is more aggressive response. Therefore, it can be concluded that the effect of the liquid holdup at the condenser change influence the tracking setpoint at the final period of batch time. In addition, the amount of product is 1.1885 kmol and its composition is 0.90884.

The liquid holdup at the plate (H_j) change: + 30% of H_j

The responses of NNMPC under the liquid holdup of the plate increasing to 30% are shown in Figure 5.15. The control action is the same as that in the nominal case, except the last period time which the manipulated variable present oscillate action. The performance of the controller in this case is 264.8487. The product quantities is 1.2101 kmol and its composition is 0.91021

The liquid holdup at the condenser (H_j) change: – 30% of H_j

Figure 5.16 are shown the response of cyclohexane composition at the condenser. The performances of this controller are 254.1220 of IAE. Observe that, the response is the same as that in the nominal case and the case of H_C increasing (see the result in the previous result), except the response in the final period of batch time which is more aggressive response. Therefore, it can be concluded that the effect of the liquid holdup at the condenser change influence the tracking setpoint at the final period of batch time. In addition, the amount of product is 1.1766 kmol and its composition is 0.90876.



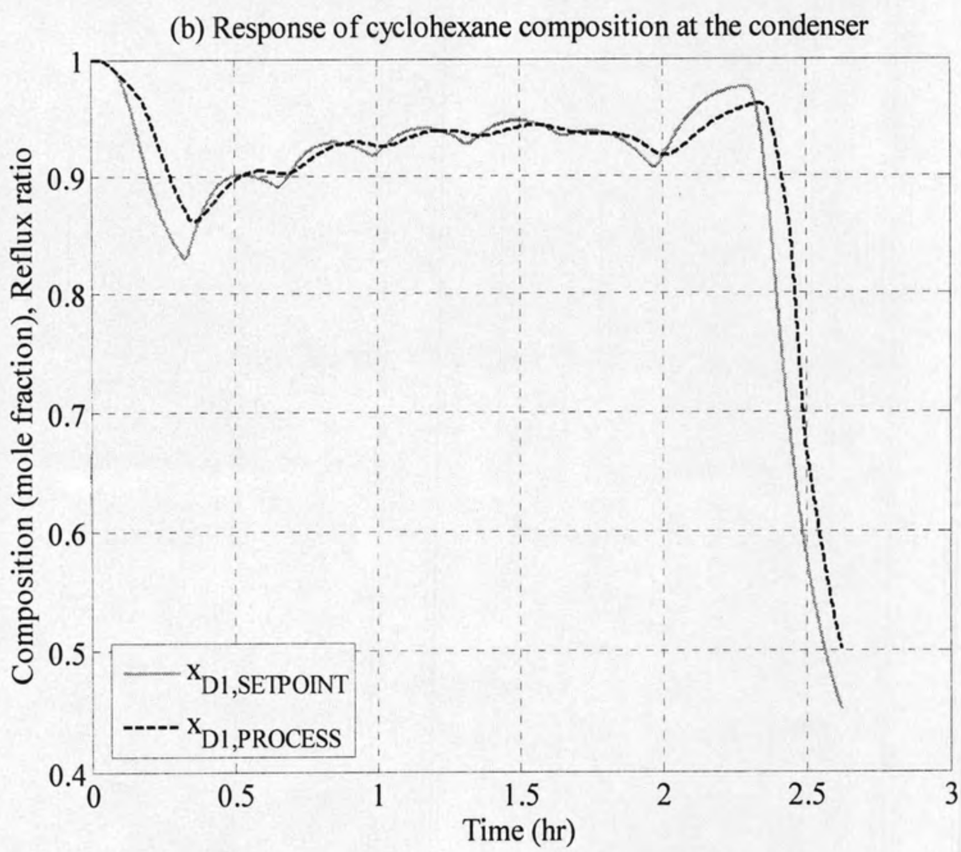


Figure 5.9 Response of Response of reflux ratio (a) and cyclohexane composition (b) under the nominal condition

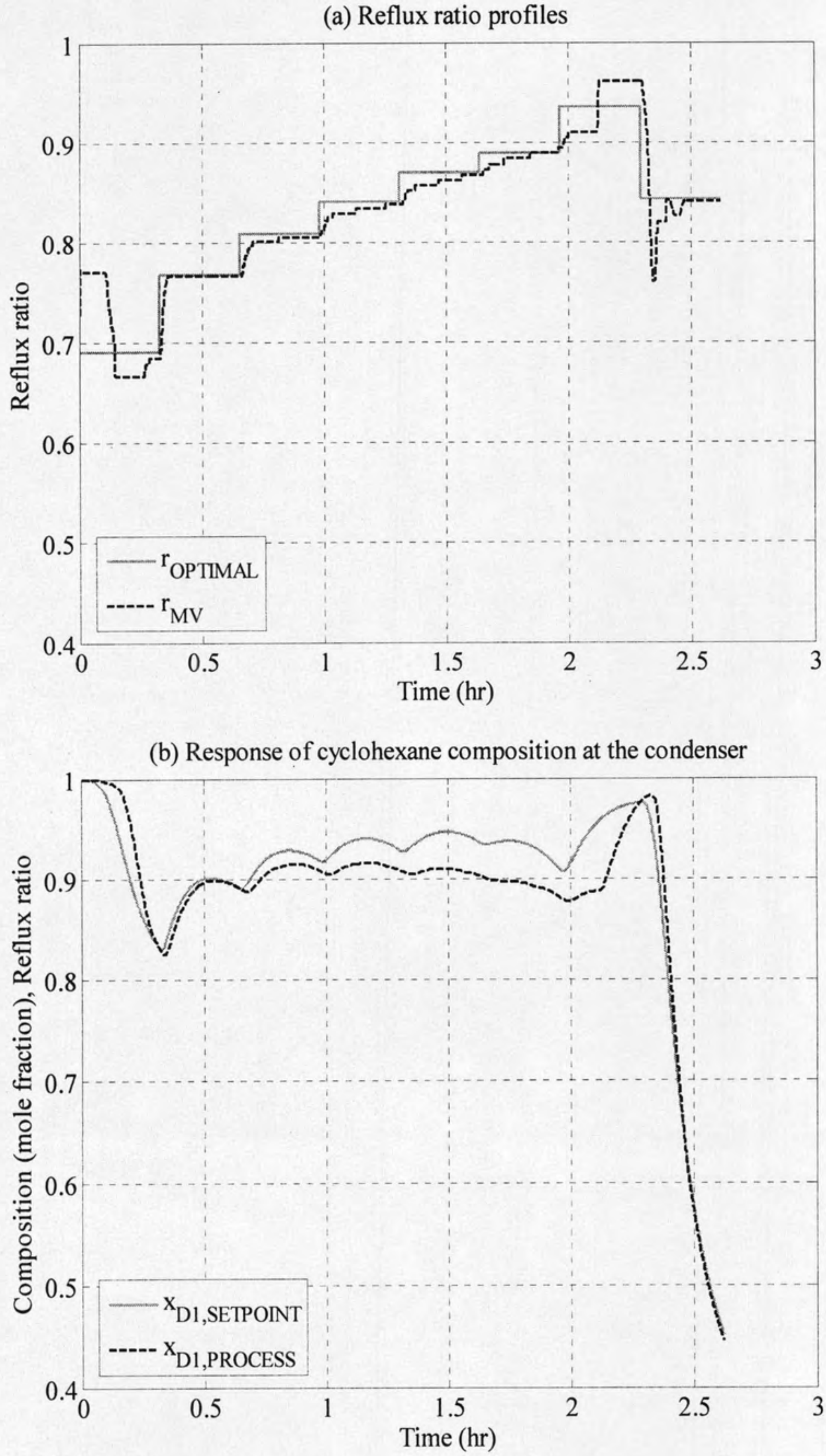


Figure 5.10 Response of reflux ratio (a) and cyclohexane composition (b) under the NN model mismatch condition

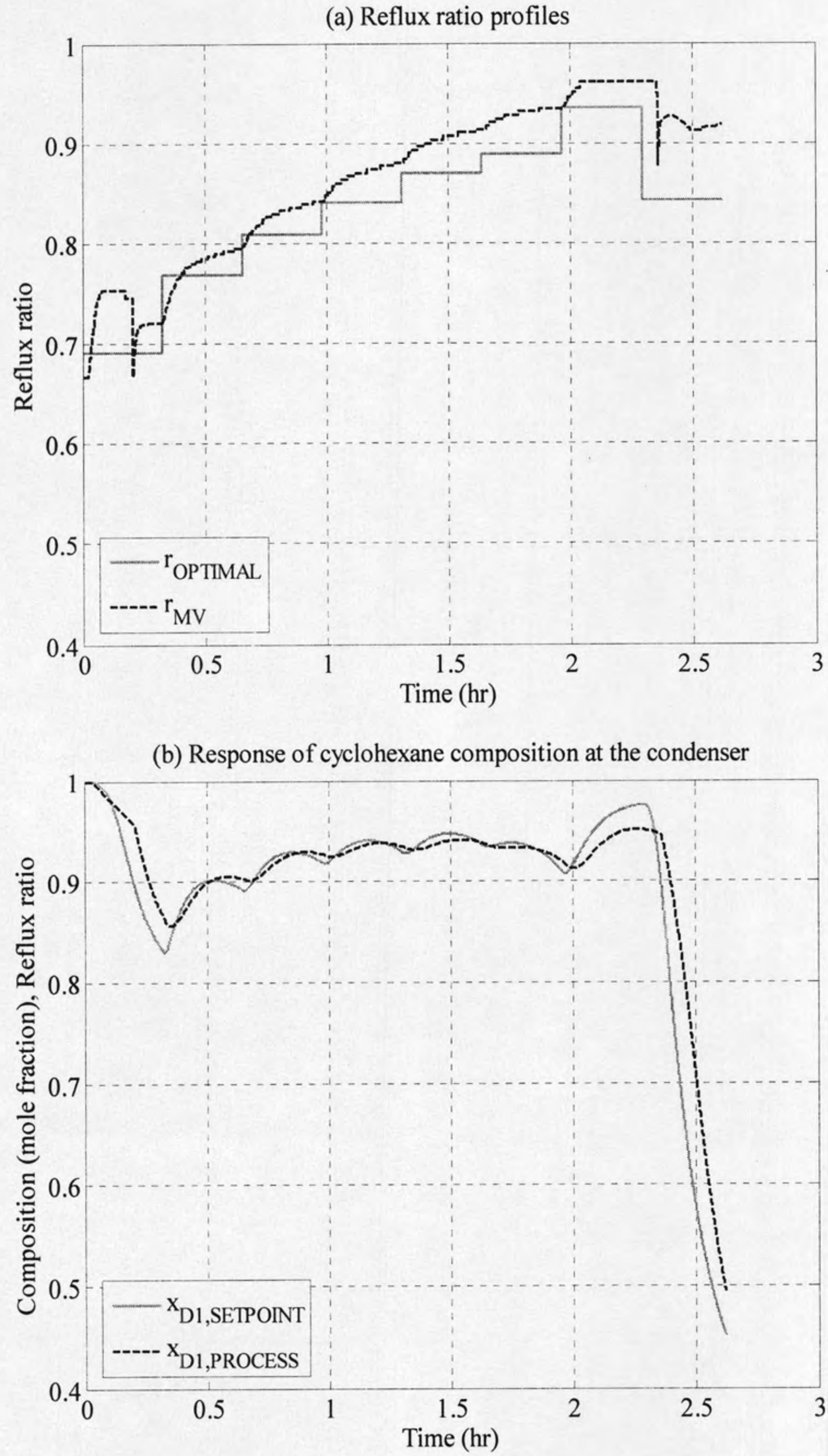


Figure 5.11 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : + 30% of V_1

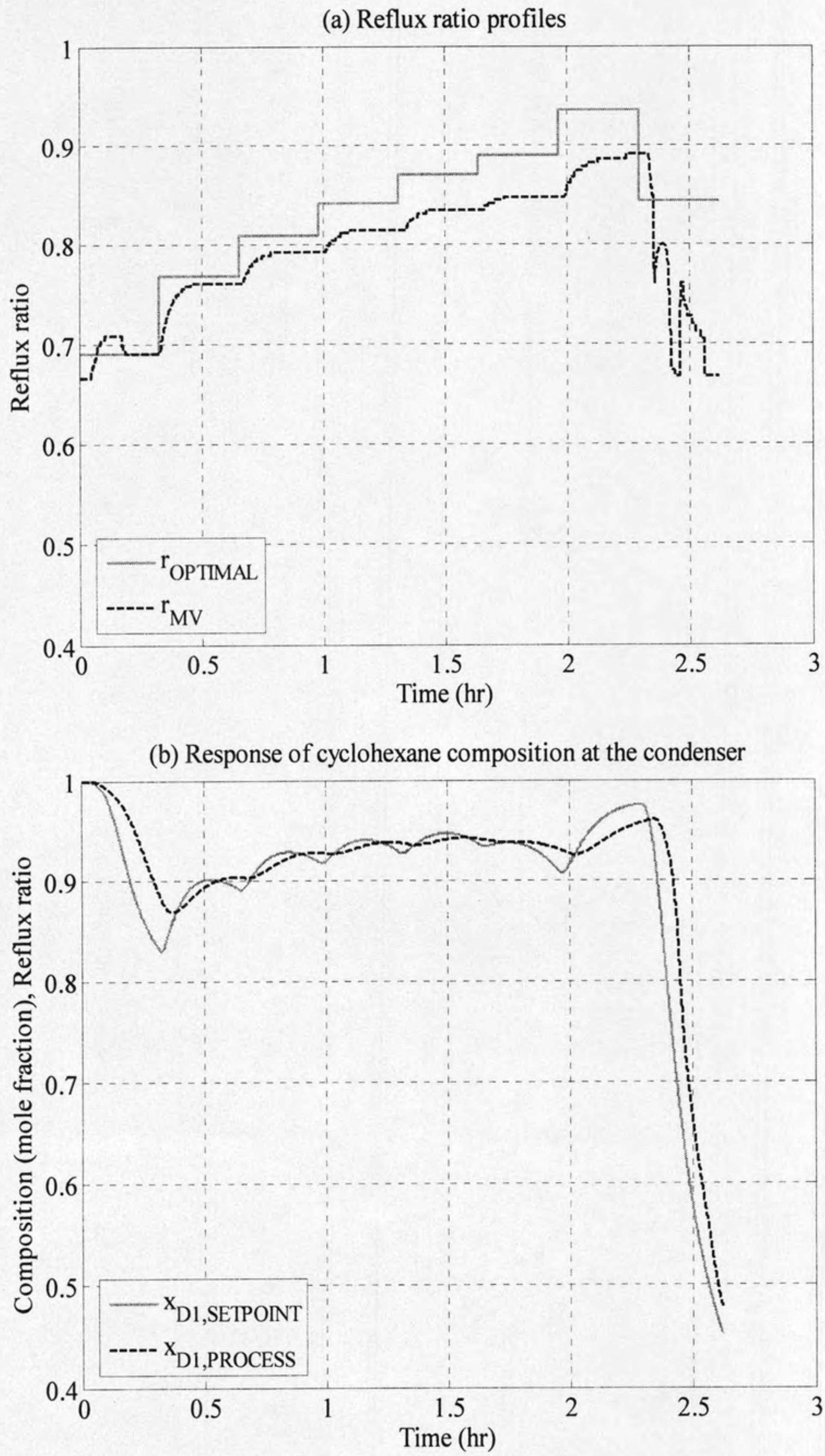


Figure 5.12 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : - 30% of V_1

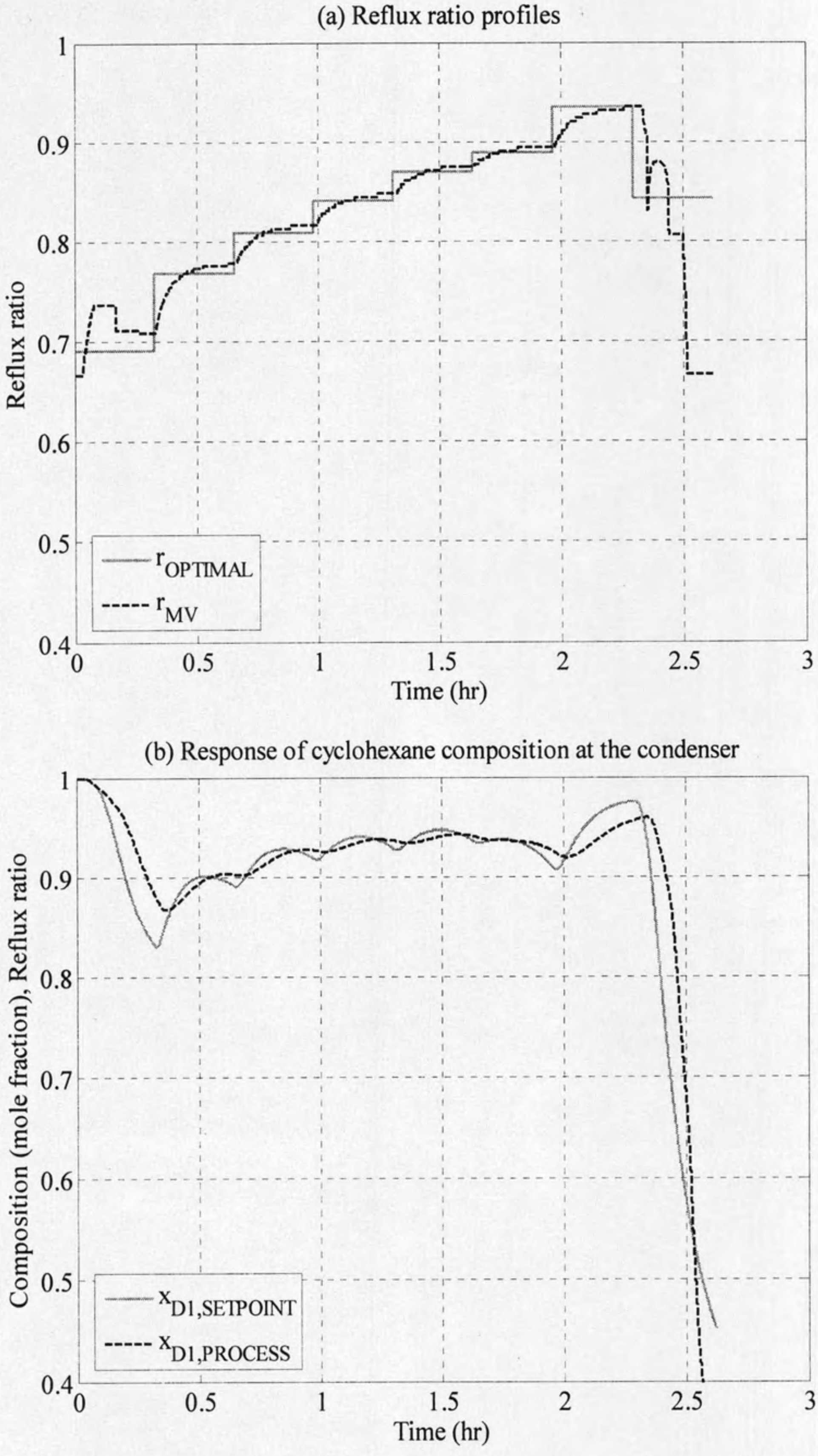


Figure 5.13 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : + 30% of H_C

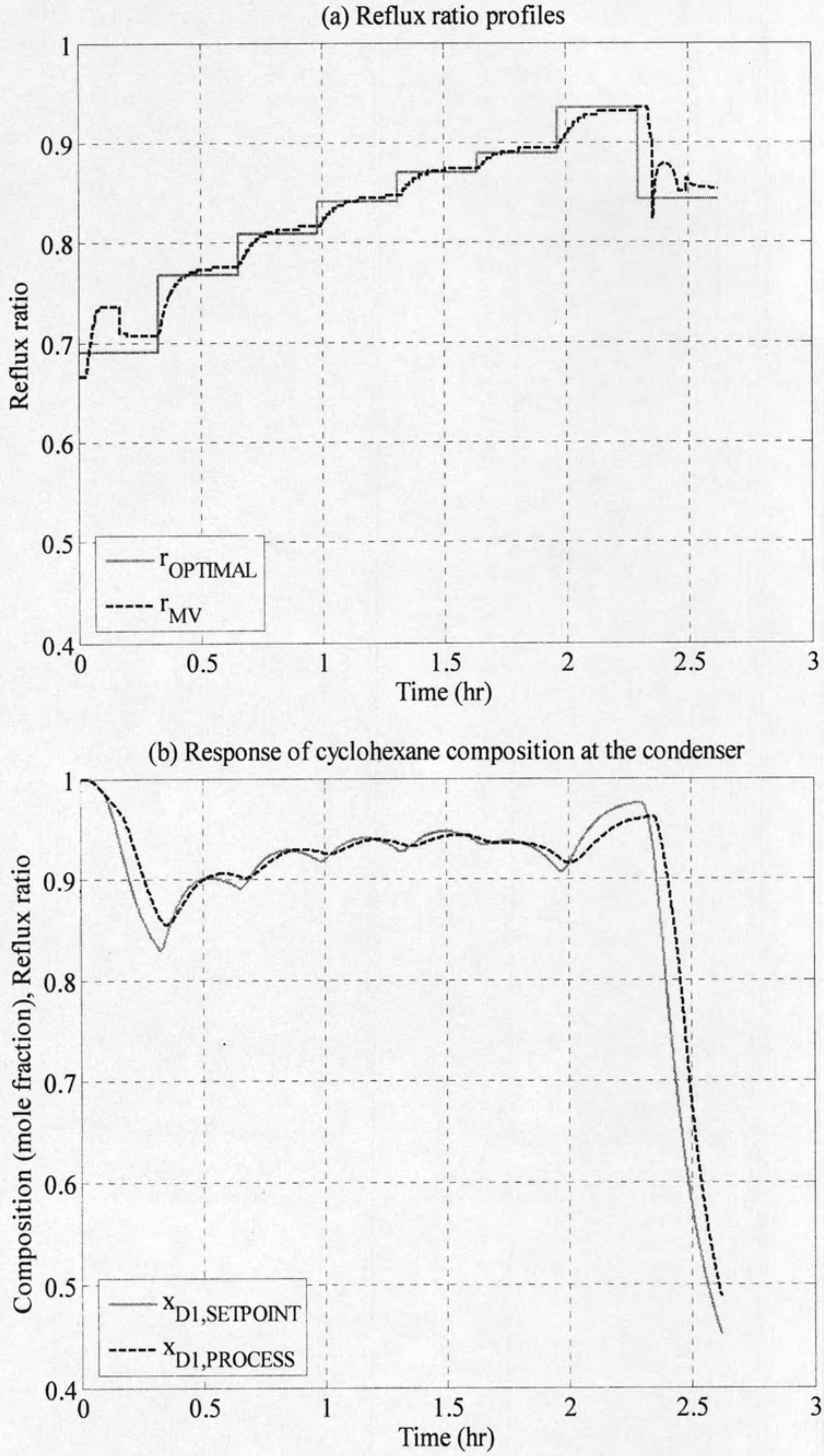


Figure 5.14 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : - 30% of H_C

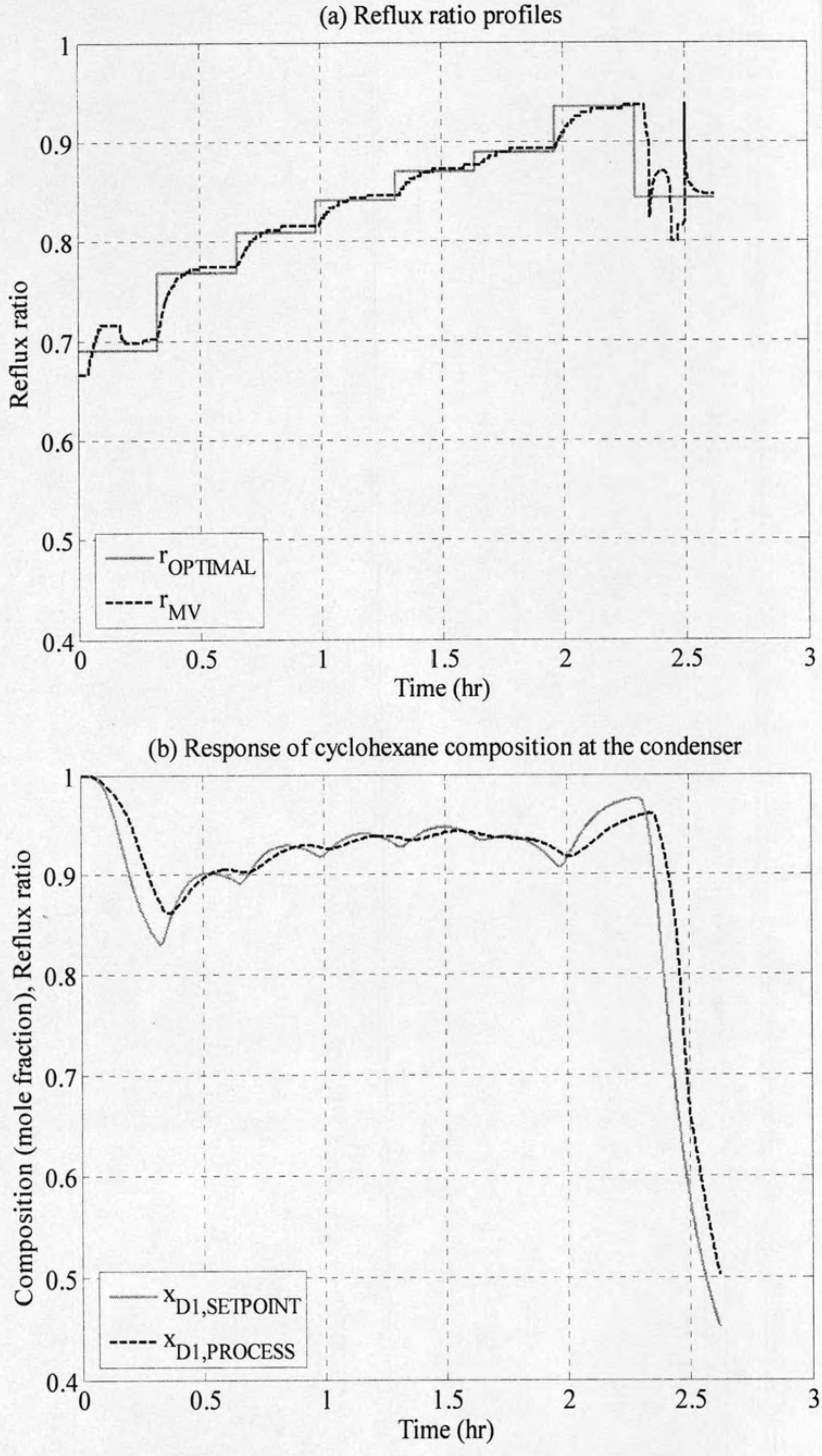


Figure 5.15 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : + 30% of H_j

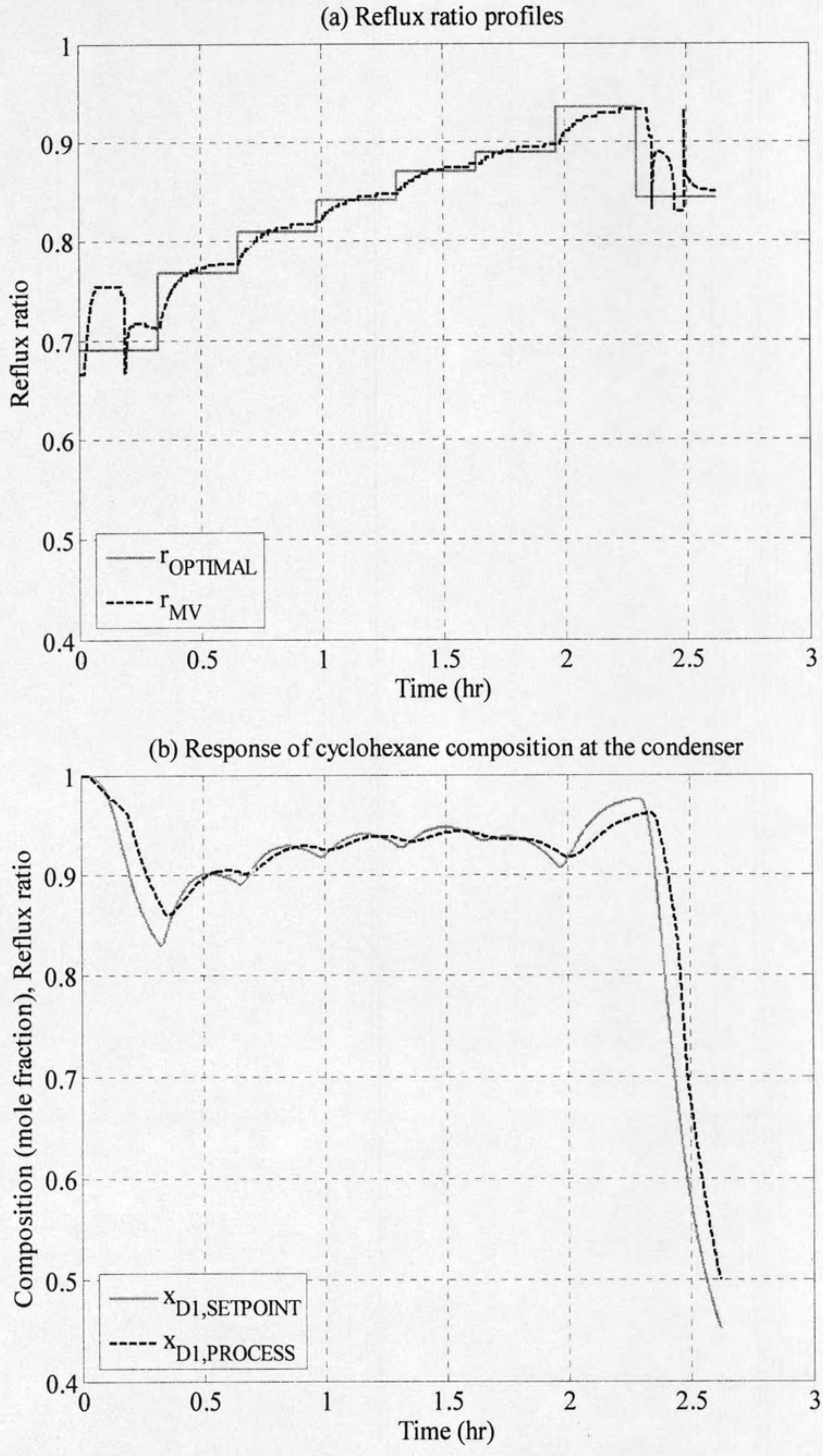


Figure 5.16 Response of reflux ratio (a) and cyclohexane composition (b) under the process mismatch condition : - 30% of H_j

Table 5.4 The performance of NNMPC for tracking the cyclohexane composition under different conditions

Case	The amount of product (kmol)	The product composition	IAE
Optimal Control	1.2199	0.895	-
Nominal	1.1933	0.90955	259.2389
NN model mismatch	1.2365	0.8848	310.5389
+ 30 % of V_l	1.2673	0.91331	255.3162
– 30 % of V_l	1.0430	0.89935	267.8650
+ 30 % of H_c	1.2558	0.88205	293.0011
– 30 % of H_c	1.1885	0.90884	231.0231
+ 30 % of H_j	1.2101	0.91021	264.8487
– 30 % of H_j	1.1766	0.90876	254.1220